IDENTIFYING FACTORS THAT MOST STRONGLY PREDICT AIRCRAFT RELIABILITY BEHAVIOR

GRADUATE RESEARCH PAPER

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Abstract

The nation's concentration on significant deficit reduction while scaling back operations in Southwest Asia will provide a new set of challenges for future DoD leaders. These challenges will require a new way of thinking. In kind, this research explores aircraft reliability from a different angle in hopes of providing clarifications to the long and challenging arena of understanding which factors most strongly predict aircraft reliability and mission performance. As the DoD shifts its focus to include the Asia Pacific region while maintaining commitments in Europe and other parts of the globe, aircraft reliability and mission performance will be crucial to maintaining an effective and efficient fleet of aircraft.

This research analyzes twelve independent qualitative variables and one dependent qualitative variable for the C-17A Globemaster III. JMP, version 10, and Excel are used to analyze data from 1 October 2009 thru 31 August 2010. Contingency Table analysis and backward stepwise logistic regression are used to determine which factors most strongly predict C-17A aircraft reliability behavior. Qualitative data is extracted from the Global Decision Support System II, Logistics, Installations and Mission Support-Enterprise View, and the Core Automated Maintenance System for Mobility/G081. The model does generate tangible statistical values but with very little practicality and suggests aircrafts monthly hours, mission type, or component status have the weakest associations with departure reliability.

Acknowledgments

I would like to thank my wonderful wife. She is truly an inspiration and runs circles around me as a mother, nurse, and full time graduate student. Thank you for enduring another move, listening to me bounce ideas off you, and making the best of every situation. Next, I would like to thank my newborn daughter. Thank you for being a great sleeper! You are amazingly beautiful and gave me a whole new perspective on life. Words cannot describe the enjoyment you provide and it's an honor to watch you grow and learn. I would also like to thank my mother-in-law. She is unselfish, compassionate, and easygoing and was instrumental in enabling me to successfully finish this program. Thank you for dropping everything and helping with the baby's daily care and needs. I know at times it was stressful and I am extremely blessed for your kindness. I can't leave out my father-in-law. As always, I am out of town when disaster strikes, so thank you for driving up to stay at the house during the hurricane and subsequent days without heat or power. Finally, I would like to thank my advisor (Dr. Johnson/AFIT), sponsor (Mr. Anderson/AMC/A9), and all the 'MOS' support staff (Mr. Becker, Ms. Traver, Ms. Bardot). I understand the time that went into making this project complete and appreciate all the guidance, encouragement, and candor throughout the entire year.

Ryan L. Theiss

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IDENTIFYING FACTORS THAT MOST STRONGLY PREDICT AIRCRAFT RELIABILITY BEHAVIOR

I. Introduction

Background

Although the main conflicts of the past decade are winding down, there will be no deliberate pause for the Air Mobility Command (AMC) to reconstitute and focus efforts on organizing, training, and equipping. According to the 2012 Department of Defense (DoD) strategic guidance, the United States will maintain an active approach to maintain the freedom of movement across the globe while being mindful of defense spending and manpower levels. As an outline for the Joint 2020 vision, it expects the DoD to be smaller and leaner. DoD focus will not abandon Middle East affairs, but will shift to include the Asia Pacific region while maintaining commitments in Europe and other parts of the globe. AMC will be integral in the strategic guidance's primary missions of counter terrorism, deter/defeat aggression, project power, counter Weapons of Mass Destruction (WMD), defend the homeland, provide a stabilizing presence, and conducting Humanitarian Disaster Relief (HDR) (DoD, 2012).

A significant challenge to achieving this strategic guidance will be the recent Congressional sequestration from the Budget Control Act (BCA) of 2011. The previous decade saw yearly increases in the defense budget and passage of wartime Overseas Contingency Operation (OCO) supplementals with relative ease. However, the essence of this Act and the recent Congressional focus on the nation's deficit have acknowledged a more confined defense budget for years to come. Specifically, the Act mandates that all spending cuts be spread evenly among discretionary and non-discretionary spending, meaning that half of the $1.2 trillion spending cuts will be derived from defense over a ten-year period (CRS, 2011).

Regardless of how the BCA shapes the DoD, air mobility will allow the U.S. flexibility to rapidly focus combat power and resources anywhere. Being the fastest transportation method, it generates the highest demand (LeMay Center/DD, 2011). Given the current fiscal landscape, limits on manpower growth, and anticipated operational demand, it is imperative that AMC uphold an effective and efficient fleet of aircraft to meet demand. Due to AMC's business characteristics, effectiveness always prevails over efficiency during combat and contingency operations and one of many methods AMC uses to identify, assess, and adjust effectiveness are metrics.

Metrics are tools that can be used to help solidify unity of effort in an attempt to improve effectiveness, spot trends, and address problems (AFLMA, 2009). As the age of aircraft fleets, deployments, and mission requirements continue to increase and manpower and funding decrease, tracking the health of the fleet will continue to be a top priority for senior leaders. Scheduled aircraft not used in the integrated air mobility system due to low reliability and mission performance degrade the delivery of vital equipment and supplies to the warfighter.

Accordingly, a recent AMC/A9 report titled *"C-17 Tail Selection, Choosing More Reliable Aircraft"* showed a significant statistical difference in reliability and mission performance among C-17A wings. The intent of the AMC/A9 report was to confirm the validity of McChord AFB's aircraft selection process, but during the analysis, uncovered some interesting differences amongst wings. Figure 1, taken from the report and titled % Breaks by Station 2004-2011, illustrates this graphically. A recommendation from this study stated, “Factor analysis should continue to examine factors which potentially predict aircraft reliability behavior and those that do not”. (HQ AMC/A9, 2012, p. 9)

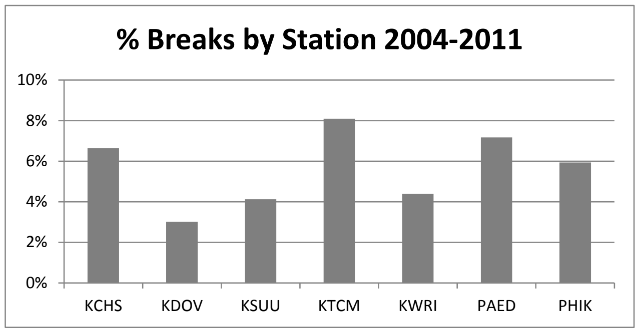


Figure 1. % Breaks by Station 2004-2011

This research will attempt to identify factors and those interactions that potentially contribute to variation in reliability and mission performance. An effort will be made to identify potential focus areas to bring unequal reliability rates back to fleet norms to prevent an interruption of materials to the warfighter in the air mobility system.

Problem Statement

What factors most strongly predict C-17A aircraft reliability behavior?

Implications

Through inductive reasoning, AMC could utilize results to fine tune the aircraft selection process across the C-17A population. Research could isolate potential root causes, indicators, and potential corrective actions. If successful, findings may be used to improve aircraft reliability and if trends are discovered, this research could be used to identify tendencies in other Mission Design Series (MDS).

Research Focus

The Graduate Research Project (GRP) will focus on investigating C-17A reliability rate and mission performance differences among wings by focusing on departure success rates. Data analysis will include qualitative factors from the command and control system for mobility airlift known as Global Decision Support System II (GDSS II) and quantitative factors from both the single entry point for viewing analytical metrics known as the Logistics, Installations and Mission Support-Enterprise View (LIMS-EV) database and the Mobility aircraft common source of all unclassified maintenance data known as Core Automated Maintenance System for Mobility/G081 (CAMS-FM/G081). Factor examples include: mission type, operating organization type, mission priority, aircraft age, delayed discrepancy rates, etc.

Assumptions/Limitations

The scope of this research will be limited to the C-17A fleet and no other MDS. The data range is from 1 October 2009 thru 31 August 2010. September 2010 data will be used to validate findings. Reliability will be gauged by the success of an on-time departure. On-time and late departures refer to the definition taken from Air Force Instruction (AFI) 11-2C-17, Volume 3 and outlines on-time departures as an aircraft has wheels off the ground no more than 20 minutes before scheduled departure or no later than 14 minutes after scheduled departure (HQ AMC/A3V, 2011). To focus the analysis on maintenance, late departures are further limited to only include applicable 900-series deviation codes for maintenance. Furthermore, personnel are qualified and trained to input data into Air Force systems and inputted data does not include misaligned metrics. Local policies, management, and leadership objectives are pursing the same metrics for the enterprise in totality.

Research Objectives/Questions

The primary objective is to identify how different factors relate to reliability and mission performance and impact AMC C-17A aircraft. The secondary objective is to empower leadership with the ability to choose more reliable aircraft for high-priority missions; ultimately increasing mission success. The researcher will attempt to answer the following questions.

1. How does AMC characterize mission reliability?
2. What factors have a significant impact on reliability?
3. Is AMC focused on the most appropriate reliability and mission performance metrics?

II. Literature Review

Chapter Overview

The literature review begins with an overview and history of the C-17A. A review of preceding reliability studies are then discussed followed by descriptions and explanations of important GDSS II, LIMS-EV, and G081 metrics.

C-17A History

The C-17A has been a workhorse delivering personnel, cargo, and equipment to main operating and forward deployed bases for the United States Air Force since its first flight in the fall of 1991. Its history dates back to the mid 1970's as the Air Force began to contemplate plans for a new airlifter to fulfill strategic airlift requirements. Other strategic airlifters such as the C-141 and C-5 were older and beginning to wear (McChord Air Museum, n.d). In addition, a new thought process in how personnel, cargo, and equipment could be delivered was starting to gain traction. The concept at the time was to have strategic aircraft take requirements from the United States to intermediate bases as close as possible to the fight. Requirements would then be loaded onto tactical aircraft such as the C-130, capable of Short Takeoff and Landings (STOL), to make its final leg into the frontlines on short and austere runways and into the hands of the warfighter. Modern technology was now capable of producing a strategic STOL airlifter that could bypass intermediate stops and fly personnel, cargo, and equipment as close as possible to the user's specified location. This concept, known as direct delivery, would complement the tactical C-130s, strategic C-5s, and retiring C-141s (LeMay Center/DD, 2011).

The USAF released a Request for Proposal (RFP) in 1979 to stimulate commercial interest and solutions into a new strategic STOL aircraft. The commercial enterprise responded with multiple options and McDonnell Douglas (later merged with Boeing) eventually emerged as the winner of the competition in 1981. The C-17A program had a rocky beginning due a multitude of problems mostly highlighted by developmental issues, cost overruns, and defense cuts. Program disputes ultimately caused 10 years between contract award and its maiden flight (Global Security, 2011). Despite an unsteady start to the program, the C-17A has become known for its reliability and maintainability and "is a major element of America's National Military Strategy and constitutes the most responsive means of meeting U.S. mobility requirements" (SAF/FMB, 2009, p. 2-1). Table 1, taken from a GAO report, shows a comparison of C-17A and C-5 characteristics (GAO, 2009).

Table 1. C-17A and C-5 Characteristics

Characteristic	C-17A	C-5
Cargo	170,900 pounds	270,000 pounds
Troops	102	81
Unrefueled range	2,700 miles	6,320 miles
Minimum runway length	3,500 feet	6,000 feet
Speed	572 mph	518 mph
Crew	3	7
Mission Capable rate (2008)	86%	52%
Cost per flying hour (2008)	$12,014	$20,947

Source: Information taken from Figure 2 (page 27) of Government Accountability Office, *Defense Acquisitions: Strategic Airlift Gap Has Been Addressed, but Tactical Airlift Plans Are Evolving as Key Issues Have Not Been Resolved.*

Reliability and maintainability are extremely important to the C-17A fleet because the program necessitates the capability to provide rapid combat power projection through a concept known as Strategic Brigade Airdrop (SBA). SBA includes both airdropping and sustaining an Army brigade-sized force in a specified time period. The airdrop requirement must be completed within 30 minutes and the airland must be completed in 24 hours. In 1980, just about the time the C-17A program was starting, the Joint Chiefs of Staff imposed the SBA requirement as a method to deliver Army forces into combat. In 1997, through the recommendation of a joint integrated product team, it became the sole SBA provider. Much of this was due to the retirement of the C-141s and limited range of the C-130s. The beginning of Operation Iraqi Freedom provides an excellent example of a previous C-17A SBA. In 2003, shortly after the operation started, 12 C-17s airdropped 1,000 troops and over the next several days consistently airlifted and sustained more than 2,000 soldiers and their equipment (O'Connor, 2005). A way to safeguard the success of future SBA operations is the continuance of C-17s reliability and maintainability distinction. A principal way to assess and measure any potential issues or trends in reliability and maintainability are metrics.

Metrics

Metrics are tools that can be used to help solidify unity of effort in an attempt to improve effectiveness, spot trends, and address problems. Metrics should be quantifiable and readily tied to the unity of effort. They provide focus and are normally characterized as leading (predictive) or lagging (historical) and provide essential data for investigation. Leading metrics such as cannibalization or discrepancies awaiting maintenance illustrate potential problems. Lagging metrics such as aircraft availability, mission capable, and not mission capable display trends (AFLMA, 2009).

Air Force Logistics Management Agency (AFLMA) pinpoints the two cornerstones of maintenance metrics for the Mobility Air Forces (MAF) as aircraft availability (AA) and departure and arrival reliability. Recognizing AA as a foundation is a recent adjustment as AFLMA specifically notes that "MC rate will no longer be the yard stick for measuring the health of the fleet…managers will utilize aircraft availability, which takes more than just MC rate into account" (AFLMA, 2009, p. 14). MC rate is a broad composite maintenance-related metric that includes Fully Mission Capable (FMC) rates and Partially Mission Capable (PMC) rates. AA is a flying-related metric that contains five subcomponents of nonavailability that include Unit Possessed Not Reported (UPNR) rates, Depot rates, Not Mission Capable Maintenance (NMCM) rates, Not Mission Capable Supply (NMCS) rates, and Not Mission Capable Both (NMCB) rates. AA provides leadership a better site picture on maintenance capability and execution flying program.

AMC measures mission reliability by tracking departure delays thru the use of two formulas. The first, Departure Reliability (DR), measures reliability regardless of cause. The command standard is 80% and is calculated by dividing the number of on-time departures by the total number of departures. The second, Deviation Accountability Rate (DAR), measures reliability by location using accountable deviations. It is calculated by dividing the number of accountable deviations by the total number of departures. "DAR provides unit-level commanders the percentage that DR would increase if those deviations did not happen" (AMC/A30C, 2010, p. 59). Units and personnel are able to assess mission reliability and trend analysis in GDSS II through the Reports Information Database Library (RIDL). The RIDL gathers data from the AMC data warehouse (ADW) which per regulation is the official analysis data source (AMC/A3OC, 2010).

The regulation also offers a five step mission reliability performance process to guide review and validation of data as shown in Table 2.

Table 2. Five-Step Mission Reliability Performance Process.

1.	Detect a change in reliability using the Deviation Accountability Rate (DAR) formula.
2.	Analyze the data to identify causal factors for the changes.
3.	Document factors impacting reliability and develop a course of action to improve departure reliability.
4.	Implement changes for improving reliability.
5.	Return to Step #1 to assess the effectiveness of implemented changes; adjust as necessary, and identify new factors affecting mission reliability.

Previous Research

Due to the recent shift and recognition of aircraft availability as the cornerstone for maintenance metrics, the majority of past research has been focused on variables which affect MC rates. Previously identified and analyzed readiness factors are normally grouped into one of six categories. Steven Oliver, et al, 2001 Air Force Journal of Logistics article titled *"Forecasting Readiness"*, does an excellent job describing these categories and interactions. They are aircraft Reliability & Maintainability (R&M), aircraft operations, logistic operations, personnel, environment, and funding. In these categories, research has showed that changes in personnel and R&M factors affect Total Not Mission Capable Maintenance (TNMCM) rates. Lower manning levels, experience, morale, and retention coupled with increased aircraft age and a change in operating conditions are linked to a decrease in TNMCM. Research also suggests that changes in logistics operations factors such as spare, inventory, and maintenance management affect Total Not Mission Capable Supply (TNMCS) rates. The supply chain not accounting for increased failures, establishing sufficient quantities of spares, inventory reduction repair process issues, and two-level maintenance are linked to a decrease in TNMCS. The last three readiness categories of funding, aircraft operations, and environment have been found to affect both TNMCM and TNMCS simultaneously verses individually. Inadequate or not properly allocated funding, increased Operations tempo (OPSTEMPO) and personnel tempo (PERSTEMPO) are linked to a decrease in both TNMCM and TNMCS concurrently (Oliver, et al, 2001).

Successively, Oliver, et al, investigated why both TNMCM and TNMCS increased during the 1990's and could MC rate be forecasted with the integration of logistics or ops-related factors thru the use of explanatory data. The forecasting model used, Funding/Availability Multimethod Allocator for Spares (FAMMAS), was time-series that only considered the significant factor of funding. The goal of this study was to produce an exploratory model that could establish potential readiness cause-and-effect relationships. It concluded that R&M established the strongest relationship and aircraft operations and logistic operations established the weakest. However, aircraft operations and logistic operations factors did provide an opportunity to create hybrid exploratory variables when combined with R&M or personnel categories. The example used was maintainers assigned per aircraft. These two showed a stronger correlation with MC rates when combined than individually (Oliver, et al, 2001).

Another study examined what impact base support resources had on AMC aircraft availability. At the time of the study, availability was not centrally defined in existing works; instead different communities (maintenance/logistics) created their own perspectives. The author defined aircraft availability as "the number of aircraft available at any time to perform a specific airlift mission or category of missions based on all pertinent operational and logistical factors." (Randall, 2004, p. 64). Using the Airfield

Simulation Tool (AST) and a 2^4 full factorial design, an analysis was accomplished to determine impacts of base support on availability and relationships between the strongest factors. The study proposed that base support factors can be grouped into the categories of maintenance capability, material handling capability, airfield characteristics, and fueling capability and are not necessarily linear with respect to airfield capacity.

Maintenance capability is principally dependent on the amount of equipment and experience of personnel. Maintenance equipment to include aircraft spares, power units, service carts, and specialized tools (both ground and support) need to be compatible with the overall airfield maintenance model. Completing cargo operations is dependent on Material Handling Equipment (MHE). MHE constraints are the type and capacity of equipment able to service aircraft. The researcher identifies 6 different types and explains the complexity of each MHE to include the importance having the right mix. Airfield characteristics include physical constraints such as runway length, operating hours, and security and fuel capability refers to storage, dispense rates, and types of equipment (pits vs. trucks). Ultimately, it suggests the relationships between the above base resources are contingent upon the demand and airfield environment. (Randall, 2004)

The challenge with researching and predicting MC rates is its integrated nature, measuring many logistical and operational processes. Another study examined, with structural equations modeling (SEM), the complex MC rate dynamic, interactions between the identified 6 readiness factors categories, and how it impacts available aircraft. The goal was to find new aircraft availability connections in uncharted areas. The report highlights the commands haphazard and inconsistent establishment of MC rate standards and notes historically that regression analysis is used the most for readiness factor investigation. Although unsuccessful in developing a model, mostly due to samples sizes, the research was successful in initiating fresh methods in modeling aircraft reliability, specifically associations with mission capable rates. (Pendley, 2006)

Aircraft reliability does not discriminate between weapon systems. Due to low C-5 TMNCM rates, the Air Force Material Command Director of Logistics (AFMC/A4) contracted AFLMA to isolate root causes of grossly underperforming TNMCM standards (Pendley, et al, 2008). The results were a series of studies published in 2008 and the use of the risk analysis methodology known as Hierarchical Holographic Model (HHM) to scope the broad subject. HHM is similar to an organizational chart with higher groups or levels at the top and each group is subdivided into smaller subgroups. “The HHM enables both a systematic and systemic framework for the problem and each submodel can be analyzed independently as well as in relationship to other submodels, with analysis of an entire HHM providing a coordinated solution to the problem” (Pendley, et al, 2008, p. 10). An example of the C-5 HHM is show in Figure 2.

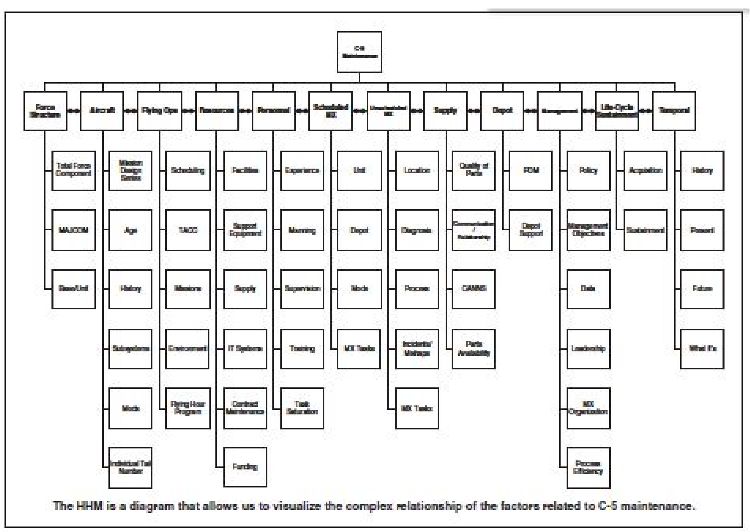


Figure 2. C-5 TNMCM Study II Hierarchical Holographic Model

After analysis of all high-level factors, to include the use of a linear decision model, ranking, and sorting of factors, personnel and complimentary goals stood out and provided "decision-quality" results. The researchers were able to peel back the onion on the authorized verses assigned ratio statistic and quantify "effective" capacity with demand. The term Net Effective Personnel (NEP) is quantified in an equation with the use of personnel availability, productivity, and training. The results allowed leadership to better place personnel with demand, which in turn reduced the TNMCM rate. The second high-level factor focuses on different perspectives along the chain of command. Researchers found at the lower levels, logistic departure reliability (LDR) as a focus while the higher levels focused on TNMCM rates. These misaligned metrics could result in a local improvement of LDR at the expense of higher strategic performance metrics (Pendley, et al, 2008).

In 2010, a research paper was written to analyze C-17A departure reliability and maintenance metrics. The researcher used linear regression analysis to identify variables and their effects on departure reliability of C-17As. Jacobs's problem statement writes, "What effects do maintenance metrics in the mission generation process have on departure reliability ("on-time" departure rates) at C-17 bases" (Jacobs, 2010, p. 2)? 10 continuous independent maintenance metrics were analyzed from similar bases that have C-17's and other Major Weapon Systems. Similar bases were defined as having single C-17 squadrons. For example, Charleston AFB was not included in the data analysis because it operates multiple C-17 squadrons. He concludes that "evidence of a moderately strong relationship between departure reliability and the maintenance metrics:

Total Not Mission Capable Supply Rate, Hourly Utilization Rate, and Average Number of Aircraft Possessed" (Jacobs, 2010, p. 35).

> Jacobs suggested future research states: Future research of both world-wide and enroute departure reliability can also be analyzed…The LIMS-EV is an application that can be used to provide a single capability to exploit information across all A4 resources to support operational, tactical, and strategic decision making. (Jacobs, 2010, 38)

This research uses some of Jacobs' suggestions by examining all C-17A departures in an 11 month period with the use of regression analysis and also looks at reliability factors in the LIMS-EV database; in addition, the research also includes qualitative factors found in the GDSS II database and analyzes departure reliability as a qualitative dependent variable instead of Jacobs method of using it as a quantitative dependent variable.

Data analysis will include qualitative factors from the command and control system for mobility airlift known as Global Decision Support System II (GDSS II) and quantitative factors from both the single entry point for viewing analytical metrics known as the Logistics, Installations and Mission Support-Enterprise View (LIMS-EV) database and the Mobility aircraft common source of all unclassified maintenance data, CAMS-FM/G081. The following section provides descriptions and explanations of important GDSS II, LIMS-EV, and CAMS-FM/G081 metrics.

Dependent Variable

Maintenance Departure Success. The dependent variable in this research is categorized as either on-time or late. Air Force Instruction (AFI) 11-2C-17, Volume 3 outlines on-time departures as an aircraft has wheels off the ground no more than 20 minutes before scheduled departure or no later than 14 minutes after scheduled departure (HQ AMC/A3V, 2011). GDSS II does not specifically categorize on-time departures but does code late deviations with a prefix of X or L. The X prefix applies when actual time departure (ATD) exceeds the deviation start time (DST) (schedule departure) by 15 minutes or more. Once a leg has been assigned an X prefix, it is then coded into one of 10 deviation categories. Any X prefix that is assigned due to aircraft maintenance is given a 900-series number. The L prefix is similar to the X prefix, however, it is due to previous leg delays such as maintenance or aircraft diverts. The L prefix notifies users that the current leg departed on-time but is still currently more than 15 minutes past the originally scheduled departure time (HQ AMC/A3OC, 2010). Therefore, in defining the dependent variable, on-time signifies GDSS II had a blank, L, or X prefix with associated delay codes outside the 900 thru 999 range. The dependent variable categorized as late signifies GDSS II was coded with an X prefix and delay code of 900 thru 999.

Independent Variables

Table 3 shows the 12 qualitative factor categories used from the collected data.

Table 3. Qualitative Factors

1. Mission Type
2. Operating Organization
3. Component Status
4. Mission Priority
5. Primary Base
6. Departure Itinerary $\leq$ 100
7. Departure Theater
8. Home Base
9. Major Command
10. Aircraft Age
11. Monthly Hours
12. Delayed Discrepancy Rate

1. Mission Type. This factor contains 8 subcategories. AMC defines mission type through the MAF Mission ID Encode/Decode Procedures. Mission types are broken down into multiple categories. A few instances (not all encompassing) are Channel missions, Special Assignment Airlift Missions (SAAM), Joint Airborne/Air Transportability Training, Contingency Missions (JA/ATT), etc., and in broad terms are characterized by who, what, when, and how airlift is accomplished. For example, a Channel mission focuses on a scheduled common user between two points. A SAAM mission focuses on special considerations with urgency and sensitivity that disqualifies the use of a Channel. A JA/ATT focuses on training operations and exercise with airborne and troop carrier units. A Contingency mission focuses on support of a specific contingency or exercises which use military operations in response to natural disasters, terrorists, or protection of U.S. interests (HQ AMC/A3OC, 2009). Multiple mission types were categorized in the original data set with the majority consisting of Channel, Contingency, Exercise, Guard Lift, JAATT, SAAM, Support, and Training.

2. Operating Organization. This variable contains 19 subcategories. The C-17A operators are universally qualified to operate all C-17A aircraft in the inventory, regardless of aircraft tail number or primary base. This provides a tremendous amount of flexibility, especially for command and control and scheduling aircraft. The variable operating organization identifies 19 different organizations and each organization does not have to "own" the aircraft to be assigned a mission. For example, Al Udeid AB and Nellis AFB do not have C-17A aircraft permanently based, however, aircrews are assigned from these locations to operate the aircraft.

3. Component Status. This factor contains 3 subcategories. Component status is user derived from the provided GDSS II data. The C-17A is operated by Active Duty, Reserve, and Guard entities. The data includes active duty assignments for Hawaii, McGuire, Al Udeid, Alaska, Dover, Charleston, Nellis, Travis, McChord, and Altus. Air National Guard assignments include Hawaii, Mississippi, and Alaska. Reserve assignments include Charleston, Travis, McChord, March, Dover, and McGuire. Its purpose is to analyze for potential abnormalities or trends between components.

4. Mission Priority. This factor contains 15 subcategories. The assignment of movement and mobility priority classification in support of the National Military Strategy is defined in Chairman of the Joint Chiefs of Staff Instruction (CJCSI) 4120.02C. The CJCSI 4120.02C delineates priority 1 missions (not all inclusive) as Presidentially directed or approved, US Forces in combat, Secretary of Defense directed, steady state contingency deployments, or redeployments. Priorities 2 thru 4 contain missions (not all inclusive) such as combat support activities, exercises, readiness or evaluation tests, JA/AAT training, static loading exercises, or static displays for public (J-4, 2011). Requests for movement of personnel, cargo, and support equipment exceed capacity which necessitates a priority system to effectively utilize DoD resources. In totality, there are 21 possible classifications. The system contains 4 categories, 1 thru 4, with each having a subcategory of A and B. Examples include in priority order of 1A, 1B, 2A, 2B, thru 4B. Each subcategory also has an additional number assigned in priority order. Examples include 1A1, 1A2, 1A3, 1B1, thru 4B3 (J-4, 2011). Multiple mission priority classifications were categorized in the original data set. Note: 3C and 5A were not

included in the CJCSI instruction on priorities. In this particular case no further research was conducted as both had less than 100 sorties and were eliminated from analysis.

5. Primary Base. Primary base is user derived from the provided GDSS II data. The purpose is to analyze for potential abnormalities or trends between primary base departures with a more robust maintenance capability vs. other departure locations with limited assets. Note: Wright Patterson AFB, OH and Stewart ANGB, NY are not included as primary base candidates. Although they are primary C-17A bases currently, they both were primary C-5 bases during the captured time horizon and therefore have are not categorized as being a primary base for the purpose of this analysis. Also, Al Udeid (OTBH) was included as a 'primary base' due to the large contingent of deployed C-17A maintenance personnel available and working to keep the aircraft and contingency operations up and running in the Southwest Asia (SWA) theater.

6. Departure Itinerary Number of 100 or less from a primary base. Departure itinerary of 100 or less from a primary base is user derived from the provided GDSS II data. Missions normally span multiple days and include a variety of legs or sorties. For ease of controllers making inputs and tracking missions, legs are followed via itinerary numbers. The initial departure leg starts at 100 and then subsequent legs are added by the 100s. For example, in the description above, the next sortie would be leg 200, and then 300, and so on. Occasionally, additional legs are added or changes are made to the original scheduled mission and these are annotated by numbers in-between (33, 250, 375, etc.). It is believed amongst aircrew members that the first leg on missions, especially homestation departures, is the hardest and most likely to have maintenance or other issues. The purpose of this factor is to analyze for potential abnormalities or trends

between departure itinerary numbers of 100 or less indicating the start of a new mission verses anything higher (mission already in-progress).

7. Departure Theater. This factor contains 6 subcategories. There are six geographic combatant commands; AFRICOM, CENTCOM, EUCOM, NORTHCOM, PACOM, and SOUTHCOM. This category captures from which theater a C-17A departs and its purpose is to analyze for potential abnormalities or trends between theaters.

8. Home Base. This factor contains 10 subcategories. The C-17A is based at many locations throughout the CONUS to include two OCONUS locations. They are operated by Air Mobility Command at Joint Base Charleston, SC; Joint Base Lewis-McChord AFB, WA; Joint Base McGuire-Dix-Lakehurst, NJ; Travis AFB, CA; and Dover AFB, DE. Pacific Air Forces operates at Joint Base Elmendorf-Richardson, AK and Joint Base Pearl Harbor-Hickam, HI. Air Force Material Command operates at Edwards AFB, CA and Air Education and Training Command operates at Altus AFB, OK. Air Force Reserve Command operates aircraft at March ARB, CA and Wright Patterson AFB, OH. Air National Guard operates at Jackson AW, MS and Stewart ANGB, NY (USAF, 2011). The purpose of this factor is to analyze for potential abnormalities or trends between bases.

9. Command. This factor contains 5 subcategories. The Major Commands (MAJCOMs) represented are Air Education and Training Command (AETC), Air Force Reserve Command (AFRC), Air Mobility Command (AMC), Air National Guard (ANG) & Pacific Air Forces (PACAF). Its purpose is to analyze for potential abnormalities or trends between commands.

10. Aircraft age (years). This factor contains 4 subcategories. Aircraft age subcategories are user derived from quantitative LIMS-EV data and are grouped into 5 years represented by < 5 years, 5 to 9 years, 10 to 14 years, and 15+ years. Age = ((Number of days since acceptance date / (365.25 x count of serial number for MDS)) (AMC/A3OC, 2010). In past research, regression analysis was accomplished to show a decline in availability with increased age on the KC-135Rs (Keating, 2003). Another study stated, "If the Air Force retains its aging fleets as planned and if those fleets' maintenance workloads and material consumption continue to grow with fleet ages…annual maintenance costs will increase and the number of aircraft available for operations and training will decrease," (Pyles, 2003, p. 183). It is assumed that a decline in availability could potentially drive an increase in late departures.

11. Monthly Hours. This factor contains 5 subcategories. Monthly hour's subcategories are user derived from quantitative LIMS-EV data and are grouped into 50 hour increments represented by < 50 hours, 50 to 99 hours, 100 to 149 hours, 150 to 199 hours, and 200+ hours. Monthly hours are the average number of hours flown per month. This variable is chosen on the assumption that more hours flown represent less maintenance repair/issues and a corresponding increase in departure success rates.

12. Delayed Discrepancy Rate (DDR). This factor contains 4 subcategories. Monthly hours subcategories are user derived from quantitative CAMS-FM/G081 data and are grouped into 10 discrepancy increments represented by < 10 discrepancies, 10 to 19 discrepancies, 20 to 29 discrepancies, and 30+ discrepancies. DDR is any non-grounding discrepancy that has been delayed or deferred and will not be worked within 24 hours from the time the discrepancy was found (AMC/A3OC, 2010).

III. Methodology

Chapter Overview

This chapter begins with a discussion on how the researcher collected and prepared data for examination. It then explores the techniques of contingency table analysis and binary logistic regression. Existing literature and personal expertise, including that of the researcher's peers, was used to help identify variables expected to influence overall C-17A fleet performance. Independent factors determined to have a noteworthy impact were chosen and data was provided by HQ AMC/A9 and gathered from U.S. Government Information Systems (USGIS). Targeted databases to acquire information were qualitative factors from the command and control system for mobility airlift, GDSS II, and quantitative factors from both the single entry point for viewing analytical metrics, LIMS-EV and the Mobility aircraft common source of all unclassified maintenance data, CAMS-FM/G081. For analysis consistency and model simplicity, quantitative factors were then grouped into qualitative categories. Statistical analysis, to include contingency tables with chi-square (χ^2) hypothesis' and regression, was accomplished with the aid of JMP version 10 software.

Data Collection and Preparation

Data collection came from three sources. The first, HQ AMC/A9, provided the researcher with a Microsoft Excel spreadsheet containing 500,000+ GDSS II missions from late September 2009 thru December 2011. GDSS II is an all-inclusive unit and force-level command and control system for mobility airlift that enable users to plan, schedule, and track all types of missions. It integrated 3 previous informational systems into one and currently provides airlift mission visibility from start thru termination anywhere in the world (AMC/News Service, 2005).

To better familiarize the researcher with GDSS II data, an account was requested. It should be noted that the process to gain access to GDSS II was cumbersome and lengthy. The researcher obtained the user account request checklist, completed the required appointment letter, and sent the appointment letter to an HQ AMC Functional Representative (ams@scott.af.mil) who then notified the researcher an account was created. To gain access, the researcher then had to send another email to Scott C2ITV User Authentication (c2itv@amc.af.mil) for a user name and password. User guides were not accessible in the GDSS II system, requiring the researcher to request access into two HQ AMC Knowledge Now Community of Practices (CoP). The first, GDSS Informational CoP (Figure 3), was required to gain access to the second, AMC C2 Systems Knowledge Management Enterprise' CoP (Figure 4) where all GDSS training materials were located.

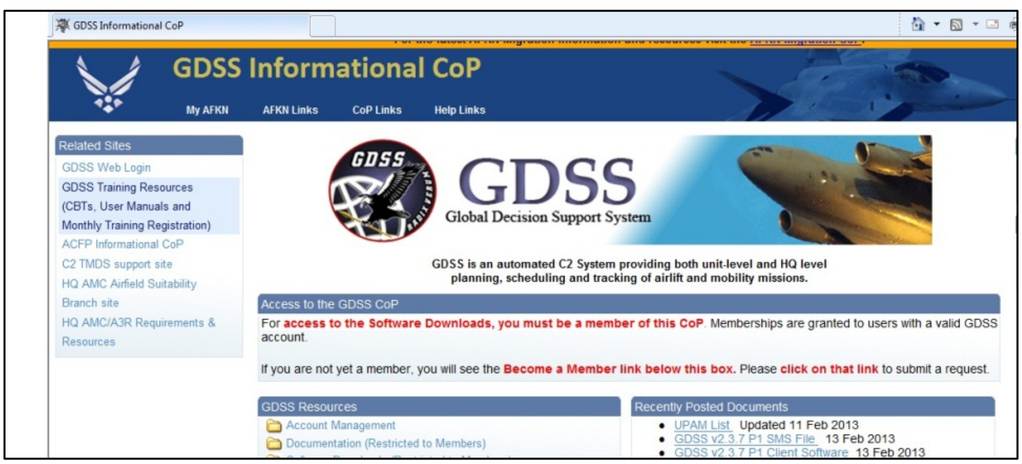


Figure 3. GDSS Information CoP

Figure 4. AMC C2 Systems Knowledge Management Enterprise CoP

As soon as GDSS II access and training materials were obtained, the researcher proceeded to narrow the GDSS II data via Excel filters and eliminated all non C-17A missions. The first filter recognized 110,000+ C-17A missions from late September 2009 thru October 2011. The researcher then proceeded to quality check the database and deleted missions with incomplete data ("blanks") or unverified cells ("None" or "Unknown"). In order to further focus the analysis on the preponderance of the data, categories in mission classifications, mission priorities, operating organization, and departure theatre with less than 100 sorties were removed. All in total, this resulted in removing less than 1 percent of the data. To minimize seasonality issues, the researcher decided to further limit the database to 1 year. The final data analyzed ranged from 1 October 09 thru 31 August 10. To validate findings, September 10 data was withheld.

The second database collection point was LIMS-EV. LIMS-EV provides:

> a single entry point on the Air Force Portal that hosts a variety of business intelligence capabilities in a flexible, dynamic Web-based environment. This capability supports reporting and analysis requirements using scorecards, and dashboards to all levels of users, whether strategic, operational or tactical. It provides near real-time metrics for weapons system availability (Petcoff, 2010).

Obtaining LIMS-EV access was accomplished by filling out an online request form (Figure 5) located at: https://www.my.af.mil/gcss-af/USAF/content/limsaccessrequest

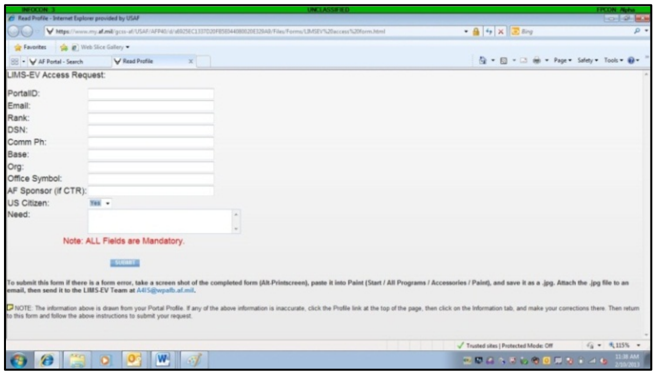


Figure 5. LIMS-EV Access Request Form

Once granted access, the researcher used filters to find applicable metrics. The following filter steps were applied: Weapon System View; Monthly Report; Report Date Range: 01-Apr-2010 through 30-September-2010 (Monthly); Report Filters: Total AF; All Theaters; All Commands; All Bases; All Types (Aircraft); All Wings/Groups/Squads; C-17; All Series/MDS; View By: serialNumber; Group By: NONE. The data was then exported into an Excel spreadsheet in order to merge with the GDSS II data.

The third database collection point was CAMS-FM/G081. CAMS-FM/G081:

> accumulates, validates, processes, stores, and makes accessible to Air Force and AMC managers the data necessary to keep AMC assigned and gained aircraft combat-ready. Worldwide logistics users connect to G081 at the SMC via the NIPRNET from desktop PCs (thick-clients)…(HAF/A4L, 2013).

Information in this database was pursued after having impromptu conversations with senior leaders about maintenance reliability. One such leader with practice as a group commander strongly alluded from experience that delayed discrepancies impacted reliability behavior. Since LIMS-EV does not display delayed discrepancy data, the researcher pursued this additional data by other means. The researcher started locally in the MOLX maintenance section at the Mobility Operations School (MOS) Expeditionary Center (EC) and was pointed towards the USAF Expeditionary Center (USAFEC) MAF Maintenance Supervision & Production Community of Practice (Figure 6).

Figure 6. USAFEC MAF Maintenance Supervision & Production CoP

From here, the researcher was able to gain access to reports at AMC that discuss leading/lagging indicators, technician skill level, proper aircraft status, and parts/equipment reliability rates and deficiencies through the Global Reach function on the HQ AMC/A4 webpage. Specifically, delayed discrepancies would be located on the HQ AMC/A4 webpage.

Once granted access to the USAFEC MAF CoP, the researcher was unable to log into the HQ AMC/A4 page (Figure 7) until a DD Form 2875, System Authorization Access Request (SAAR), was completed. This form was required because the HQ AMC/A4 pulls data from the G081 system.

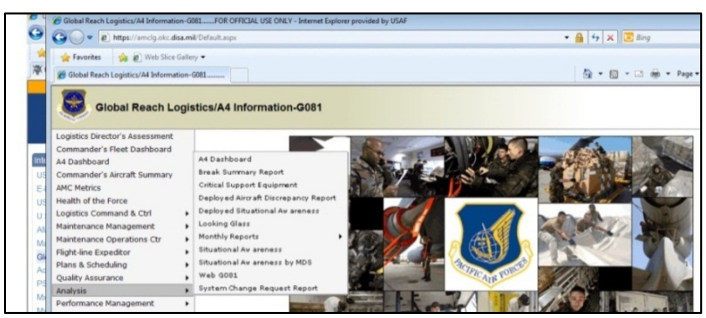


Figure 7. Global Reach Logistics/A4 Information-G081

After access was granted, the researcher found delayed discrepancy data under the Analysis/Situational Awareness tabs. The following filter steps were applied: Aircraft Type: C017A; Command: All Commands; Base: All Bases; Metrics: Delayed Discrepancies; Report Date: Monthly (Figure 8). The data was then exported into an

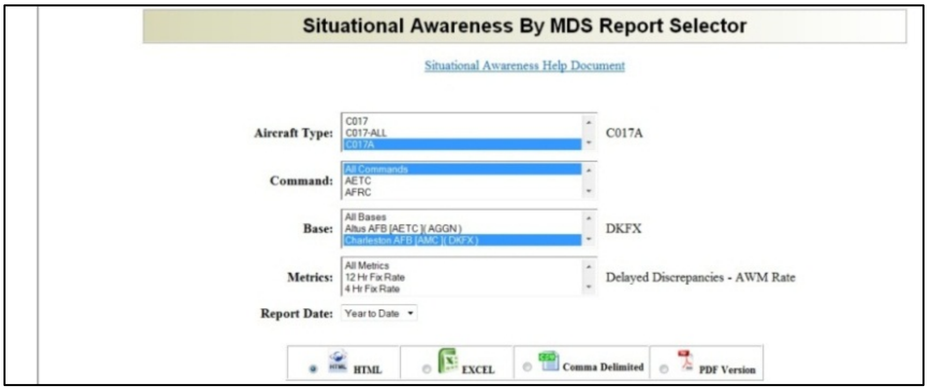


Figure 8. Situational Awareness By MDS Report Selector

Excel spreadsheet in order to merge with the GDSS II and LIMS-EV data.

Data merging had to be managed due to the use of three different databases. For example, GDSS II data displays information per mission/by day and LIMS-EV and G081 display information per tail/by month. Per mission/by day information was not available in LIMS-EV or G081. To manage this difference, the researcher first used the GDSS II data as the master Excel spreadsheet. The GDSS II data was filtered by 'Scheduled Takeoff' and then by 'Tail #'. This allowed the researcher to incorporate the LIMS-EV and G081 data as shown by the red box in Figure 9.

Scheduled Takeoff	Delay Prefix	(Y) Maintenance Departure Success	(X14) TAIL_#	(X16) Total Airframe Hours	(X19) Average Monthly Base_Delayed Discrepancy Rate
10/2/2009 1:00		On-Time	00171A	12061.8	37.4
10/3/2009 16:30		On-Time	00171A	12061.8	37.4
10/4/2009 15:00		On-Time	00171A	12061.8	37.4
10/7/2009 19:00	L	On-Time	00171A	12061.8	37.4
11/5/2009 18:15	X	Late	00171A	12158	29.2
11/5/2009 23:30	L	On-Time	00171A	12158	29.2
11/7/2009 3:45	L	On-Time	00171A	12158	29.2
11/7/2009 12:30		On-Time	00171A	12158	29.2
11/12/2009 22:30	X	Late	00171A	12158	29.2
11/15/2009 9:00	L	On-Time	00171A	12158	29.2
11/16/2009 7:15	L	On-Time	00171A	12158	29.2
11/18/2009 10:00		On-Time	00171A	12158	29.2
11/20/2009 14:15	X	Late	00171A	12158	29.2
11/24/2009 18:00		On-Time	00171A	12158	29.2
11/25/2009 3:00		On-Time	00171A	12158	29.2
12/1/2009 1:00		On-Time	00171A	12240.7	29.3
12/1/2009 7:00		On-Time	00171A	12240.7	29.3
12/13/2009 9:00	L	On-Time	00171A	12240.7	29.3
12/22/2009 18:00	X	Late	00171A	12240.7	29.3
12/23/2009 3:00		On-Time	00171A	12240.7	29.3
12/29/2009 15:00	X	Late	00171A	12240.7	29.3

Figure 9. Incorporation of databases example

The analysis into C-17A aircraft reliability and mission performance factors was separated into two phases. The first phase involved the use of contingency table analysis. The study of categorical variables is routinely accomplished with the use of contingency tables as they allow for association analysis. Figure 10 taken from a University of Florida statistics class shows a table of methods for investigating the association between variables (STA 3024).

Table 1: Methods to Investigate the Association between Variables

	Explanatory Variable(s)	*Response Variable*	*Method*
Chapter 3	Categorical	Categorical	Contingency Tables
Chapter 4	Categorical	Quantitative	Analysis of Variance (ANOVA)
Chapter 5 and 6	Quantitative	Quantitative	Regression Analysis
	Quantitative	Categorical	(not discussed)

Figure 10. Methods to Investigate the Association between Variables

Further analysis, such as the complex patterns of association was addressed in the second phase with multiple binary logistic regression.

Contingency Tables

After data collection and before logistic regression was accomplished, the researcher analyzed chosen factors for independence using two-way contingency tables as described by the textbook, Statistics for Business and Economics, Eleventh Edition. (McClave, et al., 2011, 535)

<u>χ^2-Test for Independence</u>

H_o: The two classifications are independent.
H_a: The two classifications are dependent.

Test statistic: $\chi^2 = \sum \frac{[n_{ij} - \hat{E}_{ij}]^2}{\hat{E}_{ij}}$ (1)

where $\hat{E}_{ij} = \frac{R_i C_j}{n}$

Rejection region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r-1)(c-1) degrees freedom (df)

<u>Conditions Required for a Valid χ^2-Test: Contingency Table</u>

1. The *n* observed counts are a random sample from the population of interest.

2. The sample size, *n*, will be large enough so that, for every cell, $\hat{E}_{ij}$, will be > 5.

<u>In the context of this research:</u>

n_{ij} = Denotes observed frequency of the cell in row *i* and column *j*
$\hat{E}_{ij}$ = Denotes expected frequency of the cell in row *i* and column *j*
R_i = Row count (R) dependent variable ($_i$)
C_j = Column count (C) independent variable ($_j$)
n = total sample size

The chi-square hypothesis, also known as two-way analysis, tests the independence of two qualitative variables. Although this test demonstrates if a relationship exists, it does not demonstrate causality. Another caution of the chi-square test is analyzing results when expected cell counts are low (< 5) and must be avoided (Warr, 2013). During analysis, the researcher confirmed all expected cell counts exceed this minimum. The chi-square test is functional, even though the researcher may not believe independence to be true, because it allows for the prediction of expected frequencies based on the postulation the variables ‘are’ independent. By knowing the observed and expected frequency count, the researcher is then able to assess the significance of the differences by using the equation 1 test statistic. The researcher then sets the criteria to reject the null hypothesis of independence (Crawley, 2013). All chi-square tests in this research are considered at the .05 significance level. In phase two of the analysis, contingency table and chi-square test results of association will be used to make a multivariate logistic model.

Binary Logistic Regression

The second phase will involve regression analysis. Regression analysis is a popular statistical technique utilized to analyze relationships among variables. This researcher used multiple binary logistic regression in an attempt to predict the success rate of departure reliability. In the analysis, departure reliability is a dichotomous variable of either on-time or late. This type of regression is suitable because it is more flexible than linear regression and discriminant analysis which are limited to continuous variable predictors and may have values of less than 0 (Pace, 2012). The benefits of logistic regression over linear regression are its more relaxed and flexible assumptions, modeling the probability of the outcome, not changes in the outcome itself, and its bounded function (Chatterjee, 2006).

IV. Results and Analysis

Chapter Overview

This chapter discusses individual variable analysis and provides charts and tables for the contingency tables analysis and logistic regression models developed during this research.

Model Development

JMP, 10 version, is used for the statistical analysis of the variables and data. Figure 11 shows the consolidated Fit Y to X summary per variable. All independent variables, except Major Command, showed sufficient evidence at the .05 significance level to reject the null hypothesis of independence. Major Command was therefore not used in subsequent analysis.

Factor	DF	Pearson(P) χ^2	Prob>χ^2	Critical Value of χ^2.05	P χ^2 > CV
(X1) Mission Type	7	213.212	<.0001	14.0671	✓
(X1a) Mission Type	3	133.894	<.0001	7.81473	✓
(X1b) Mission Type	1	34.545	<.0001	3.84146	✓
(X2) Operating Organization	18	215.157	<.0001	28.8693	✓
(X2a) Operating Organization	2	101.474	<.0001	5.99147	✓
(X3) Component Status	2	12.281	<.0001	5.99147	✓
~~(X3a) Component Status~~	~~1~~	~~3.705~~	~~0.0543~~	~~3.84146~~	✗
(X4) Mission Priority	14	233.52	<.0001	23.6848	✓
(X4a) Mission Priority	1	113.129	<.0001	3.84146	✓
(X5) Primary Base	1	288.297	<.0001	3.84146	✓
(X6) Departure Itinerary < 100	1	110.945	<.0001	3.84146	✓
(X7) Departure Theater	5	427.536	<.0001	11.0705	✓
(X7a) Departure Theater	2	246.522	<.0001	5.99147	✓
(X7b) Departure Theater	1	147.16	<.0001	3.84146	✓
(X8) Home Base	9	105.989	<.0001	16.919	✓
(X8a) Home Base	2	76.453	<.0001	5.99147	✓
~~(X9) Major Command~~	4	~~6.422~~	~~0.1698~~	~~9.48773~~	✗
(X10) Age	3	113.62	<.0001	7.81473	✓
(X11) Monthly Hours	4	48.178	<.0001	9.48773	✓
(X12) Delayed Discrepancy Rate	3	68.495	<.0001	7.81473	✓

Figure 11. Fit Y (Mission Departure Success) by X Summary

During the chi-square analysis for independence, it was recognized that some sub-categories dominated the data when more than two variables were present. For example, mission type passed the initial independence test with eight subcategories. Of these eight subcategories, contingency mission represented the preponderance of data with 48% and exercise mission represented the least data count with less than .03% (Figure 12). To simplify the model and create a more equal distribution, sub-variables with minimal counts were combined into a new category named ‘other’ (Figure 13). After each new category was created, independence tests were again accomplished. If sufficient evidence to reject the null hypothesis of independence remained, a reevaluation of the distribution was accomplished to try and reach the simplest model and to avoid any one subcategory from dominating the preponderance of the data (Figure 14). Figures 12-14 are just one example and show progression of consolidating the mission type category.

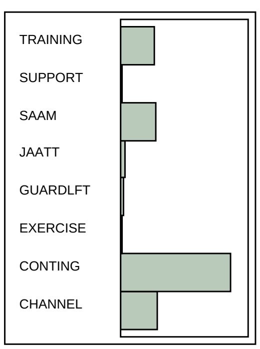


Figure 12. Mission Type

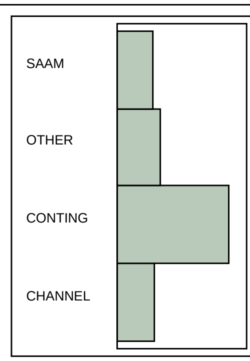


Figure 13. Mission Type-1a

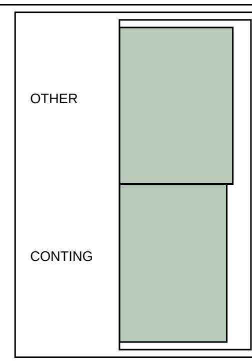


Figure 14. Mission Type-1b

Component status was the only independent variable with multiple subcategories that did not provided sufficient evidence to reject the null hypothesis of independence during subsequent reevaluation and chi-squared testing. Therefore, no ‘other’ category was made for this independent variable. Full detailed analysis of Figure 11 (distribution, frequencies, expanded X by Y contingency table, and tests) are located in Appendix A.

Once each independent sub-variable was finalized, the researcher analyzed descriptive statistics to review characteristics of the data. A review of the data, Appendix B, shows a majority of the departures are with active duty crews, on 1B1 missions, without primary maintenance, not initial takeoffs, with aircraft less than 10 years of age, with aircraft averaging 100 to 200 hours per month, and with aircraft that have on average 10 thru 29 written delayed discrepancies per month. Variables without the preponderance of departures but with the preponderance of late departures include contingencies, super bases (Charleston and McChord), Reserves, primary maintenance locations, initial departures, and aircraft ages from 10 to 14 years.

The contingency table and descriptive statistics analysis shows dependence and associations, but it does not give a sense to the strength of associations. Figure 15 acts as the researchers starting point into the strength of association. It sorts the chi-squared test for independence results from Figure 11 from the most significant variable to the least significant and is the standard order for Figures 16 thru 19 for comparison purposes.

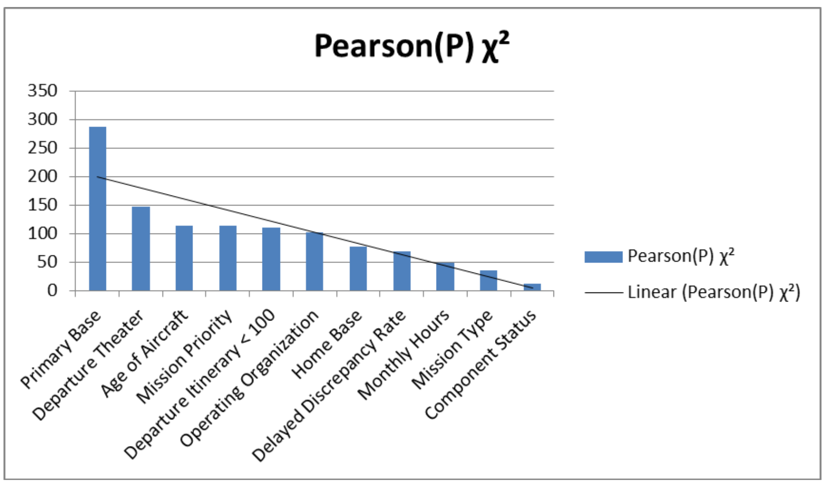


Figure 15. Pearson Chi-Squared results

One common technique in determining the strength of association is the relative risk ratio. When the ratio of proportions is equal to 1, the association is weakest. The researcher uses the percentage of late departures as the control element in the proportion. Using primary base (availability of robust maintenance) as an example, the relative risk is determined by dividing the proportion of 'No' primary base lates (4.95%) by 'Yes' primary base lates (9.21%), resulting in a ratio of .53. For variables that contained more than two subcategories, relative risk was calculated by taking the aggregate. For example, if a variable contained 3 subcategories, relative risk was calculated by dividing subcategory 1 by 2, 1 by 3, and 2 by 3 and then dividing the relative risk 1 thru 3 summation by 3. Using the same order as the chi-squared test, one would expect to see an increase in the relative risk (decrease in strength of association) and this is confirmed by Figure 16.

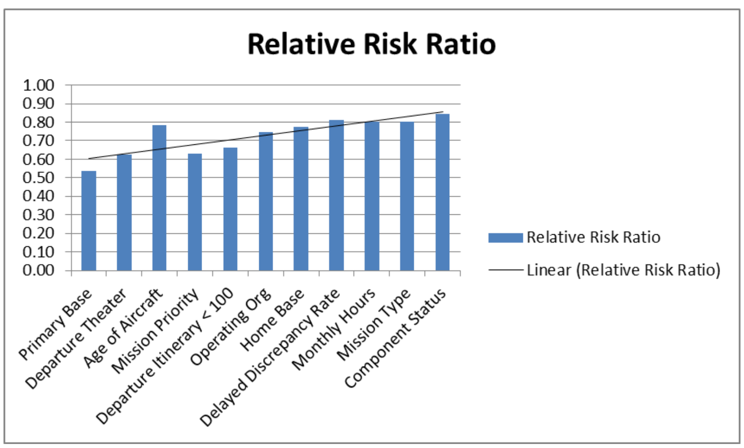


Figure 16. Relative Risk Ratio results

The next technique used to determine the strength of association was examining Rsquare(U) (Figure 17). According to the JMP help file, "values of the Rsquare (U) (sometimes denoted as R2) range from 0 to 1. High R2 values are indicative of a good model fit, and are rare in categorical models."

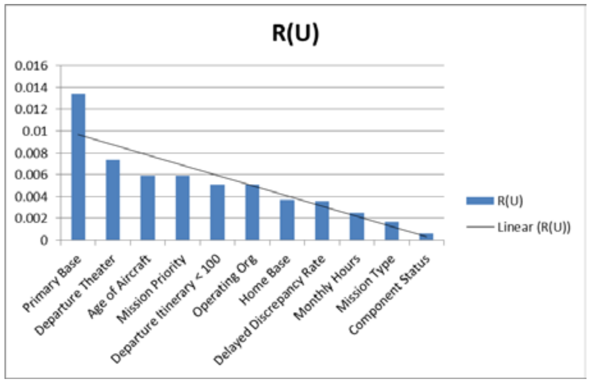


Figure 17. R(U) results

Notwithstanding the notice about rare high values for categorical models, the trend is consistent with the Pearson and Relative Risk results.

Another measure of the model fit is the Akaike information criterion (AIC) (Figure 18). JMP explains this strength of association as "This value may be compared with other models to determine the best-fitting model for the data. The model having the smallest value, as discussed in Akaike (1974), is usually the preferred model (JMP help file)". Again, using the same variable order, a clear increasing trend is noticeable.

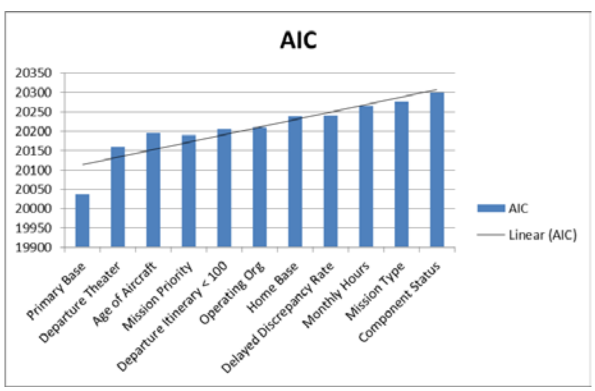


Figure 18. AIC results

The last goodness of fit measure is the Receiver Operating Characteristic (ROC) curve (Figure 19). JMP explains this measure as "The area under the curve is the indicator of the goodness of fit, with 1 being a perfect fit (JMP help file)". Figure 18 shows the consolidated values of ROC curves for each variable and is once more consistent with the other strength of association indicators. Overall, the individual variables of Primary Base and Departure Theater displayed the strongest associations and mission type and component status show the weakest associations.

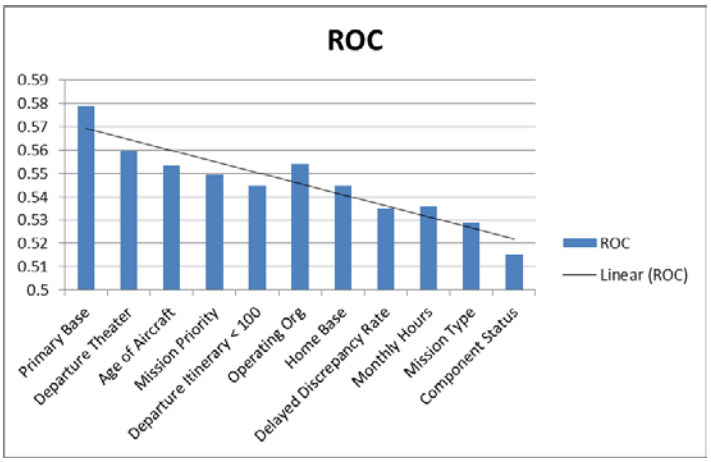


Figure 19. ROC results

With a better sense of association strengths, the researcher used JMP's Analyze Fit Model to perform a backward stepwise regression to find the most parsimonious model. In order to better control and monitor the stepwise regression steps, the researcher assigned the factor subcategories nominal values by coding dummy variables. These dummy variables were then incorporated as new 'factors' into the data set. For example, Operation Organization contained 3 subcategories after the chi-square analysis/consolidation and dummy variable coding assignment is show in Table 4. All independent variables went through the same coding steps.

Table 4. Dummy Variable coding example

Operating Organization	Dummy Variable
Super Base	0 0
Other	1 0
385 AEG	0 1

After coding the factors, the researcher ran the first stepwise regression with every factor resulting in a full model coefficient of determination, RSquare (U), of 5.51% (Figure 20 & 21).

Journal: Untitled 2 - JMP

Nominal Logistic Fit for (Y) Maintenance Departure Success

Converged in Gradient, 6 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	559.880	21	1119.76	<.0001*
Full	9593.060			
Reduced	10152.940			

RSquare (U)	0.0551
AICc	19230.1
BIC	19420.8
Observations (or Sum Wgts)	42979

Figure 20. JMP output for the model - all independent variables

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-3.1380165	0.175383	320.14	<.0001*
(X1b) Mission Type	0.25786917	0.0545069	22.38	<.0001*
(X2a) Operating Organization_Other	0.17386229	0.0667881	6.78	0.0092*
(X2a) Operating Organization_385AEG	-0.1336821	0.0715958	3.49	0.0619
(X3) Component Status_Guard	-0.2744712	0.1103553	6.19	0.0129*
(X3) Component Status_Active Duty	0.00949719	0.0537281	0.03	0.8597
(X4a) Mission Priority	1.10062852	0.0615226	320.05	<.0001*
(X5) Primary Base? 2	-0.6946777	0.063179	120.90	<.0001*
(X6) Departure Itinearary < 100	-0.0909612	0.0687101	1.75	0.1856
(X7b) Departure Theater	-0.8488319	0.0641964	174.83	<.0001*
(X8a) Home Base_KTCM	0.11271225	0.0858981	1.72	0.1895
(X8a) Home Base_KCHS	0.01338949	0.0982025	0.02	0.8915
(X10a) Age of Aircraft_5 to 9	0.27331877	0.0619005	19.50	<.0001*
(X10a) Age of Aircraft_10 to 14	0.30782409	0.0705247	19.05	<.0001*
(X10a) Age of Aircraft_15+	0.26263288	0.0809982	10.51	0.0012*
(X11) Average Monthly Hours Flown_50 to 99	0.06959371	0.1235549	0.32	0.5733
(X11) Average Monthly Hours Flown_100 to 149	0.19179231	0.1210113	2.51	0.1130
(X11) Average Monthly Hours Flown_150 to 199	0.07504543	0.124774	0.36	0.5475
(X11) Average Monthly Hours Flown_200+	-0.0149249	0.1361087	0.01	0.9127
(X12) Average Monthly Base_Delayed Discrepancy Rate_10 to 19	-0.3152879	0.1233197	6.54	0.0106*
(X12) Average Monthly Base_Delayed Discrepancy Rate_20 to 29	0.15288932	0.1444794	1.12	0.2900
(X12) Average Monthly Base_Delayed Discrepancy Rate_30+	-0.0065685	0.1395258	0.00	0.9625

Figure 21. JMP output Full Model Parameter Estimates - all independent variables

The researcher then proceeded to remove variables, starting with the highest that did not fit into the model at the .05 significance level. The removed variables and corresponding model values after each iteration are displayed in Table 5. The researcher

Table 5. JMP Reverse selection output - extracted to an Excel table

Iteration	DF	ChiSquare	ChiSquare Δ	Prob>ChiSq	R(U)	R(U) Δ	AICc	AICc Δ	Highest Prob>ChiSq Variable	Discarded Variable for Next Iteration
1	21	1119.76	0	<.0001	0.0551	0	19230	0	0.9625	Delayed Discrepancy Rate_30+
2	20	1119.758	0.002	<.0001	0.0551	0	19228.1	1.9	0.911	Previously discarded + MHF_200+
3	19	1119.745	0.013	<.0001	0.0551	0	19226.2	1.9	0.8927	Previously discarded + Home base_KCHS
4	18	1119.727	0.018	<.0001	0.0551	0	19224.2	2	0.8657	Previously discarded + Component Status_AD
5	17	1119.698	0.029	<.0001	0.0551	0	19222.2	2	0.2743	Previously discarded + MHF_50 to 99
6	16	1118.501	1.197	<.0001	0.0551	0	19221.4	0.8	0.3761	Previously discarded + MHF_150 to 199
7	15	1117.718	0.783	<.0001	0.055	0.0001	19220.2	1.2	0.177	Previously discarded + Departure Itinerary ≤ 100
8	14	1115.882	1.836	<.0001	0.055	0	19220	0.2	N/A	N/A

stopped removing factors once all P-Values in the model remained below a .05 significance level and no further improvement in the RSquare (U) and AICc were observed. This resulted in a coefficient of determination, RSquare (U), of 5.50%. To control for Type 1 errors or false positives and complete the analysis, the Bonferroni method was used and an experimentwise error rate was determined with the remaining variables.

The textbook, Statistics for Business and Economics, Eleventh Edition describes the need to use a smaller significance level when testing individual variables and "to make the probability of at least one failure equal to α, we must specify the individual levels of significance to be less than α" (McClave, et al., 2011, 472). With 14 variables at the .05 significance level, the new individual significance level was .0036 (.05/14). Three of the 14 variables had significance levels above this value and were therefore removed from the model. Sequential corrections were not needed since the Bonferroni correction with 11 variables resulted in a significance level of .0045 (.05/11) and the same three of the 14 variables had significance levels the .0045 value. After the correction the resulting coefficient of determination, RSquare (U), was 5.38% with a significance of <.0001 and

ROC of 0.67. The remaining categories that contained variables in the regression were Mission Type, Operating Organization, Mission Priority, Primary Base, Departure Theater, Home Base, Aircraft Age, Monthly Hours, and Delayed Discrepancy Rate.

September 2010 data was withheld from the above analysis to validate findings. However, it is expected with such a low coefficient of determination and Receiver Operating Characteristic that any validation will be low and without a substantial level of confidence. JMP's 'Save Probability Formula', which provides a prediction of the most likely response given certain parameters, confirms this by only predicting the proper September late departures 4% of the time. Given the current parameters and lack of logistic regression success, any further analysis with the current data set would not be profoundly meaningful or advance research into departure reliability. The model does generate tangible statistical values but with very little practicality.

V. Conclusions and Recommendations

Chapter Overview

This chapter summarizes the research accomplished in the preceding sections and discusses the outcomes related to the questions proposed in the introduction. It also highlights recommendations for future research.

Problem Statement and Research Questions

As the DoD shifts its focus to include the Asia Pacific region while maintaining commitments in Europe and other parts of the globe, aircraft reliability and mission performance will be crucial to maintaining an effective and efficient fleet of aircraft. The nation's concentration on significant deficit reduction while scaling back operations in Southwest Asia will provide a new set of challenges for future DoD leaders. These challenges will require a new way of thinking. In kind, this research sought to explore factors at a different angle in hopes of providing clarifications to the long and challenging arena of aircraft reliability and mission performance. It also sought to provide a new avenue into potential future research. The research questions guiding this endeavor were:

1. How does AMC characterize mission reliability?
2. What factors have a significant impact on reliability?
3. Is AMC focused on the most appropriate reliability and mission performance metrics?

Question one was discussed in the literature review and provided a reference point for the researcher to engage the topic. AMC approaches mission reliability with a high degree of importance as they use multiple methods to assess success. In whole, it is process-oriented and tracked thru the use of two different formulas, Departure Reliability and Deviation Accountability Rate. This first is set at a command standard of 80% and measures reliability regardless of cause while the second measures reliability by location using accountable deviations. AMC also gives commanders a way to evaluate performance in the form of a five-step cyclical process and they steer personnel to measure mission reliability and trend analysis in the Reports Information Database Library (RIDL). The mission reliability performance process and reports database are key to maintaining reliability integrity.

Question two is a logical follow on to question one and focuses on what factors have a significant impact on reliability. The literature review summarizes previous research subjects and attempts at exploring factors that predict aircraft reliability. All have come to the conclusion that no one single factor is the shining beacon towards a direct cause and effect relationship. Aircraft reliability is complex due to its integrated nature, measuring many logistical and operational processes. Using a common regression approach with a different angle (logistic), this researcher was unsuccessful with any level of fidelity at furthering attempts to find new linkages or create a new model for aircraft reliability. Though, the researchers statistical evidence suggests with regularity that an aircraft's monthly hours, mission type, or component status have the weakest associations with departure reliability.

Question three asked if AMC focused on the most appropriate reliability and mission performance metrics. AMC uses previous aircraft reliability research to focus regulations and databases on the most appropriate reliability and mission performance metrics. The third step of the AMC mission reliability performance process emphasizes documenting factors and developing courses of action but does not give any guidance on which are the best factors to document. The command follows metrics such as MC rates, AA rates, TNMCM rates, and such. Nonetheless, the aim of this research was to give commanders a potential new set of factors to document which potentially predict aircraft reliability behavior. Due to the lack of 'new' answers in question two, question three cannot be entirely answered or used to recommend AMC to shift focus from current metrics.

Recommendations for Future Research

The lack of model practicality or validation should not deter use of logistic regression in future research to identify how different factors relate to reliability and mission performance. Instead, it should act as a catalyst for future research. The combinations of variable selection, time scales, and Major Weapons Systems are abundant and may lead to a different outcome. This particular research focused on the C-17A which has a relatively high departure reliability rate and is comparatively new associated to other AMC aircraft in the inventory. It also narrowed the variable selection to only qualitative characteristics. Future research can incorporate a mixture of both qualitative and quantitative variables with virtual straightforwardness.

With the use of Contingency Table Analysis, the research did highlight some association strengths and future research should focus on the variables with the greatest dependencies. Furthermore, finding no associations can sometimes provide useful insights. AMC is considering the removal of USAF aircraft tail flashes because these tail flashes brand aircraft as a particular wing's assets, and the elimination will change their status to overall general USAF aircraft assets. The proposed reasoning behind this initiative is to simplify the management of aircraft as they age and this research may bolster this argument. However, in the researcher's opinion, additional study will be needed to substantiate any new initiative to determine the 'humanism' tail flash influence on maintenance personnel.

Final Thoughts

To ease further researchers efforts in data collection, senior leaders should champion a streamlined process for admittance to unclassified databases and metrics. For example, to access GDSS II, personnel must go through a technology-mediated service encounter. According to the book Service Management, Operations, Strategy, Information Technology, 7th edition, a technology-mediated service encounter is "the customer and human service provider are not physically co-located and thus the service encounter no longer is the traditional face-to-face contact. Communication is usually enabled by a voice telephone call to access service…" (Fitzsimmons, 2011, p. 97) With GDSS II, units and personnel are able to assess mission reliability and trend analysis through the RIDL. However, to obtain access to this database library, personnel must go through multiple steps or "hurdles".

Step 1 – Obtain user account request checklist
Step 2 – Complete Appointment letter
Step 3 – Sent letter to Unit/CC (O-5 or above) to have sign
Step 4 – wait for reply
Step 5 – Send letter to ams@scott.af.mil (do not accept fax or scanned documents)
Step 6 – wait for reply
Step 7 – AMS Function Rep will notify the user via email when account is created
Step 8 – Send that email to c2itv@amc.af.mil to request user name and temp password
Step 9 – wait for reply
Step 10 – Log in (must change password every 60 days or account is frozen)
Step 11 – Obtain data

While a technology-mediated service encounter may benefit certain types of services, such as making restaurant reservations, it is not the right type of technology service encounter for internal Air Force customers. For the Air Force, the main problem with this type of exchange is the economics of waiting and frustration associated with the lack of trust. It can be measured by unproductive time and waiting, the creation of anxiety, and other emotional miseries. The GDSS II example indicated this by noting 3 separate "wait for reply" actions, 7 self-service actions and 4 different "servers". This can be alleviated by moving further down the technology service encounter scale to a technology-generated service encounter (self-service). Using the same GDSS II example, the new process would be:

Step 1 – log into GDSS II with secure Common Access Card (CAC)

Step 2 – obtain data

All Air Force personnel are issued a CAC with a computer chip imbedded. This chip contains specific information such as name, certificates, etc. In order to access any Air Force server such as the Air Force Portal, personnel must use their issued CAC and linked user 6 digit personalized pin number. It is recommended that this is the only requirement to access Air Force metrics. This step alone would eliminate labor costs for nonproductive activity (re-screening personnel for access). The implemented technology-generated service encounter would eliminate all "servers" and the "wait for reply" steps. Not to mention that the implications for managers are non-significant.

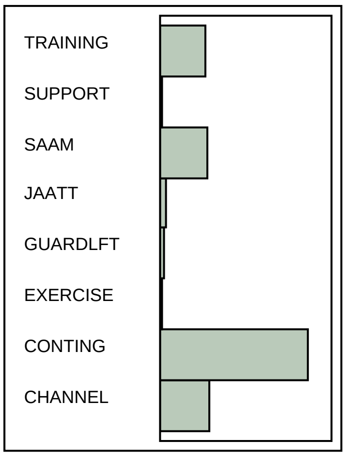
They are non-significant because Air Force Personnel have already been exposed to this via different systems. For example, some systems where the internal customer can control the experience and navigate information are the Defense Travel System, Leave Web & Leave and Earnings Statements. In short, the overall level of readiness of the internal customer base is excellent. If the Air Force decides to not eliminate labor costs for nonproductive activity (re-screening personnel for access), these personnel could spend more time facilitating and coaching users of the databases. This technology-generated approach would provide internal customers a better sense of empowerment and trust. The researcher will end with a statement by Max Planck, a German theoretical physicist, on his initial 'journeys' before discovering energy quanta; "An indispensable hypothesis, even though still far from being a guarantee of success, is however the pursuit of a specific aim, whose lighted beacon, even by initial failures, is not betrayed (JOC/EFR, 2006)".

Appendix A: Contingency Table Analysis

Round 1 thru 20; Maintenance Departure Success vs. Independent Variables

Round 1 Mission Type (X1)

(X1) Distribution



(X1) Frequencies

Level	Count	Prob
CHANNEL	7153	0.16643
CONTING	20986	0.48828
EXERCISE	168	0.00391
GUARDLFT	443	0.01031
JAATT	843	0.01961
SAAM	6725	0.15647
SUPPORT	308	0.00717
TRAINING	6353	0.14782
Total	42979	1.00000

(X1) By (Y) Contingency Table

Count Total % Col % Row % Expected Deviation Cell Chi^2	Late	On-Time	

CHANNEL	491 1.14 18.02 6.86 453.522 37.4779 3.0971	6662 15.50 16.55 93.14 6699.48 -37.478 0.2097	7153 16.64
CONTING	1479 3.44 54.28 7.05 1330.58 148.423 16.5564	19507 45.39 48.46 92.95 19655.4 -148.42 1.1208	20986 48.83
EXERCISE	15 0.03 0.55 8.93 10.6517 4.34829 1.7751	153 0.36 0.38 91.07 157.348 -4.3483 0.1202	168 0.39
GUARDLFT	26 0.06 0.95 5.87 28.0876 -2.0876 0.1552	417 0.97 1.04 94.13 414.912 2.08755 0.0105	443 1.03
JAATT	10 0.02 0.37 1.19 53.4488 -43.449 35.3197	833 1.94 2.07 98.81 789.551 43.4488 2.3910	843 1.96
SAAM	469 1.09 17.21 6.97 426.386 42.6144 4.2590	6256 14.56 15.54 93.03 6298.61 -42.614 0.2883	6725 15.65
SUPPORT	43 0.10	265 0.62	308 0.72

	1.58 13.96 19.5281 23.4719 28.2120	0.66 86.04 288.472 -23.472 1.9098	
TRAINING	192 0.45 7.05 3.02 402.8 -210.8 110.319	6161 14.33 15.31 96.98 5950.2 210.8 7.4681	6353 14.78
	2725 6.34	40254 93.66	42979

<u>(X1) Tests</u>

N	**DF**	**-LogLike**	**RSquare (U)**
42979	7	124.84186	0.0123

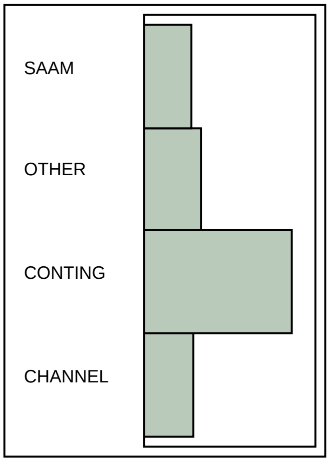
Test	**ChiSquare**	**Prob>ChiSq**
Likelihood Ratio	249.684	<.0001*
Pearson	213.212	<.0001*

$H_\circ$: Departure success (Y) is independent of Mission Type (X1)
H_a: Departure success (Y) is dependent (related to) Mission Type (X1)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 213.212$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 7df = 14.0671;
  - -- 213.212 > 14.0671; therefore -- strong evidence against $H_\circ$

Round 2 Mission Type (X1a)
- Combined SUPPORT, JAATT, GUARDLFT, EXCERCISE into OTHER

(X1a) Distribution



(X1a) Frequencies

Level	Count	Prob
CHANNEL	7153	0.16643
CONTING	20986	0.48828
OTHER	8115	0.18881
SAAM	6725	0.15647
Total	42979	1.00000

(X1a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
CHANNEL	491 1.14 18.02 6.86	6662 15.50 16.55 93.14	7153 16.64
CONTING	1479 3.44 54.28 7.05	19507 45.39 48.46 92.95	20986 48.83
OTHER	286 0.67 10.50	7829 18.22 19.45	8115 18.88

	3.52	96.48	
SAAM	469 1.09 17.21 6.97	6256 14.56 15.54 93.03	6725 15.65
	2725 6.34	40254 93.66	42979

<u>(X1a) Tests</u>

N	**DF**	**-LogLike**	**RSquare (U)**
42979	3	76.335382	0.0075

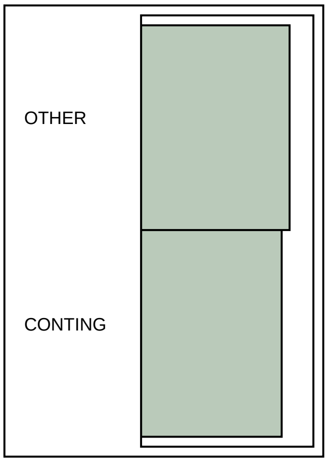
Test	**ChiSquare**	**Prob>ChiSq**
Likelihood Ratio	152.671	<.0001*
Pearson	133.894	<.0001*

$H_{\circ}$: Departure success (Y) is independent of Mission Type (X1a)
H_a: Departure success (Y) is dependent (related to) Mission Type (X1a)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 133.894$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 3df = 7.81473;
  - -- 133.894 > 7.81473; therefore -- strong evidence against $H_{\circ}$

Round 3 Mission Type (X1b)
- Further combined SAAM and CHANNEL into OTHER

(X1b) Distribution



(X1b) Frequencies

Level	Count	Prob
CONTING	20986	0.48828
OTHER	21993	0.51172
Total	42979	1.00000

(X1b) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
CONTING	1479 3.44 54.28 7.05	19507 45.39 48.46 92.95	20986 48.83
OTHER	1246 2.90 45.72 5.67	20747 48.27 51.54 94.33	21993 51.17
	2725 6.34	40254 93.66	42979

(X1b) Tests

N	DF	-LogLike	RSquare (U)

N	DF	-LogLike	RSquare (U)
42979	1	17.277094	0.0017

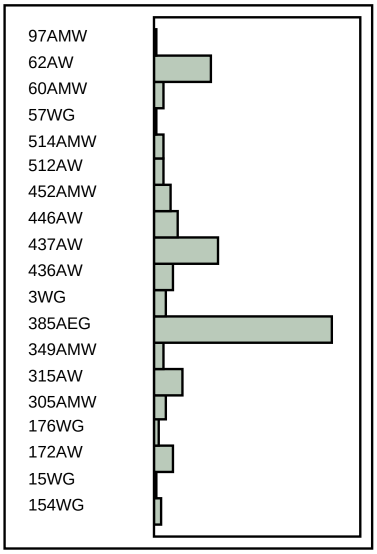
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	34.554	<.0001*
Pearson	34.545	<.0001*

$H_\circ$: Departure success (Y) is independent of Mission Type (X1b)
H_a: Departure success (Y) is dependent (related to) Mission Type (X1b)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 34.545$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 1df = 3.84146;
  - -- 34.545 > 3.84146; therefore -- strong evidence against $H_\circ$

Round 4 Operating Organization (X2)

(X2) Operating Organization Distribution



(X2) Frequencies

Level	Count	Prob
154WG	578	0.01345
15WG	237	0.00551
172AW	1596	0.03713
176WG	445	0.01035
305AMW	1143	0.02659
315AW	2459	0.05721
349AMW	741	0.01724
385AEG	15737	0.36616
3WG	1032	0.02401
436AW	1623	0.03776
437AW	5749	0.13376
446AW	2124	0.04942
452AMW	1573	0.03660
512AW	851	0.01980
514AMW	898	0.02089
57WG	214	0.00498
60AMW	858	0.01996
62AW	5007	0.11650
97AMW	114	0.00265
Total	42979	1.00000

(X2) By (Y) Contingency Table

Count Total % Col % Row % Expected Deviation Cell Chi^2	Late	On-Time	
154WG	32 0.07 1.17 5.54 36.647 -4.647 0.5893	546 1.27 1.36 94.46 541.353 4.64697 0.0399	578 1.34
15WG	12 0.03 0.44 5.06 15.0265 -3.0265 0.6096	225 0.52 0.56 94.94 221.973 3.02652 0.0413	237 0.55
172AW	85 0.20 3.12 5.33 101.191 -16.191 2.5907	1511 3.52 3.75 94.67 1494.81 16.1913 0.1754	1596 3.71
176WG	27 0.06 0.99 6.07 28.2144 -1.2144 0.0523	418 0.97 1.04 93.93 416.786 1.21436 0.0035	445 1.04
305AMW	111 0.26 4.07 9.71 72.4697 38.5303 20.4856	1032 2.40 2.56 90.29 1070.53 -38.53 1.3868	1143 2.66

315AW	200 0.47 7.34 8.13 155.908 44.0919 12.4695	2259 5.26 5.61 91.87 2303.09 -44.092 0.8441	2459 5.72
349AMW	30 0.07 1.10 4.05 46.9817 -16.982 6.1381	711 1.65 1.77 95.95 694.018 16.9817 0.4155	741 1.72
385AEG	772 1.80 28.33 4.91 997.774 -225.77 51.0876	14965 34.82 37.18 95.09 14739.2 225.774 3.4584	15737 36.62
3WG	88 0.20 3.23 8.53 65.432 22.568 7.7839	944 2.20 2.35 91.47 966.568 -22.568 0.5269	1032 2.40
436AW	96 0.22 3.52 5.91 102.903 -6.9032 0.4631	1527 3.55 3.79 94.09 1520.1 6.90316 0.0313	1623 3.78
437AW	354 0.82 12.99 6.16 364.504 -10.504 0.3027	5395 12.55 13.40 93.84 5384.5 10.5042 0.0205	5749 13.38
446AW	149 0.35	1975 4.60	2124 4.94

	5.47 7.02 134.668 14.3319 1.5253	4.91 92.98 1989.33 -14.332 0.1033	
452AMW	97 0.23 3.56 6.17 99.733 -2.733 0.0749	1476 3.43 3.67 93.83 1473.27 2.73301 0.0051	1573 3.66
512AW	55 0.13 2.02 6.46 53.956 1.044 0.0202	796 1.85 1.98 93.54 797.044 -1.044 0.0014	851 1.98
514AMW	82 0.19 3.01 9.13 56.9359 25.0641 11.0336	816 1.90 2.03 90.87 841.064 -25.064 0.7469	898 2.09
57WG	6 0.01 0.22 2.80 13.5683 -7.5683 4.2215	208 0.48 0.52 97.20 200.432 7.56825 0.2858	214 0.50
60AMW	52 0.12 1.91 6.06 54.3998 -2.3998 0.1059	806 1.88 2.00 93.94 803.6 2.39982 0.0072	858 2.00
62AW	475 1.11 17.43 9.49	4532 10.54 11.26 90.51	5007 11.65

	317.459 157.541 78.1806	4689.54 -157.54 5.2924	
97AMW	2 0.00 0.07 1.75 7.22795 -5.2279 3.7814	112 0.26 0.28 98.25 106.772 5.22795 0.2560	114 0.27
	2725 6.34	40254 93.66	42979

<u>(X2) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	18	103.43267	0.0102

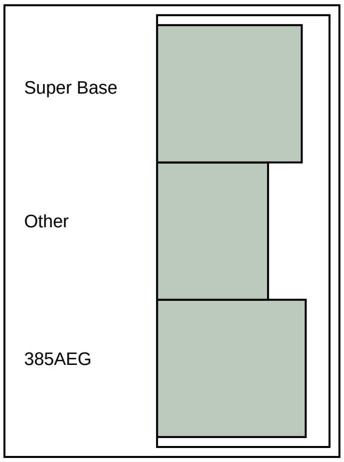
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	206.865	<.0001*
Pearson	215.157	<.0001*

H_o: Departure success (Y) is independent of Operating Organization (X2)
H_a: Departure success (Y) is dependent (related to) Operating Organization (X2)

- $\chi^2=\Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- α = .05
  - -- χ^2 = 215.157; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 18df = 28.8693;
  - -- 215.157 > 28.8693; therefore -- strong evidence against H_o

Round 5 Operating Organization (X2a)
- Combined Charleston/McChord AFB Active Duty/Reserve Organizations into Super Base and all others except 385AEG into Other

(X2a) Distribution



(X2a) Frequencies

Level	Count	Prob
385AEG	15737	0.36616
Other	11903	0.27695
Super Base	15339	0.35690
Total	42979	1.00000

(X2a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
385AEG	772 1.80 28.33 4.91	14965 34.82 37.18 95.09	15737 36.62
Other	775 1.80 28.44 6.51	11128 25.89 27.64 93.49	11903 27.69
Super Base	1178 2.74 43.23	14161 32.95 35.18	15339 35.69

	7.68	92.32	
	2725 6.34	40254 93.66	42979

<u>(X2) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	2	51.527642	0.0051

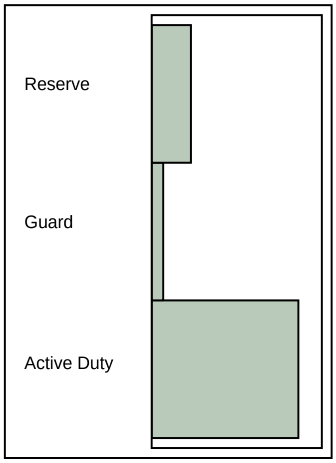
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	103.055	<.0001*
Pearson	101.474	<.0001*

$H_\circ$: Departure success (Y) is independent of Operating Organization (X2a)
H_a: Departure success (Y) is dependent (related to) Operating Organization (X2a)

- $\chi^2=\Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 101.474$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 2df = 101.474;
  - -- 101.474 > 5.99147; therefore -- strong evidence against $H_\circ$

Round 6 Component Status (X3)

(X3) Distribution



(X3) Frequencies

Level	Count	Prob
Active Duty	31714	0.73790
Guard	2619	0.06094
Reserve	8646	0.20117
Total	42979	1.00000

(X3) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
Active Duty	1968 4.58 72.22 6.21	29746 69.21 73.90 93.79	31714 73.79
Guard	144 0.34 5.28 5.50	2475 5.76 6.15 94.50	2619 6.09
Reserve	613 1.43 22.50 7.09	8033 18.69 19.96 92.91	8646 20.12
	2725	40254	42979

	6.34	93.66		

(X3) Tests

N	DF	-LogLike	RSquare (U)
42979	2	6.0708738	0.0006

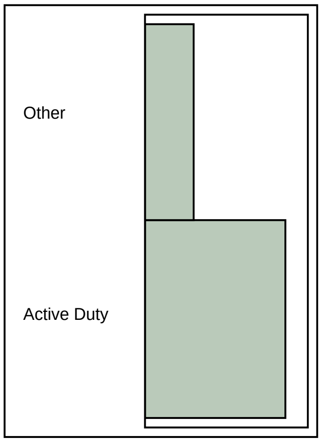
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	12.142	0.0023*
Pearson	12.281	0.0022*

$H_{\circ}$: Departure success (Y) is independent of Component Status (X3)
H_a: Departure success (Y) is dependent (related to) Component Status (X3)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- $\alpha = .05$
  -- $\chi^2 = 12.281$; P-value <.0001*
  -- $\chi^2_{.05}$ @ 2df = 5.99147;
  -- 12.281 > 5.99147; therefore -- strong evidence against $H_{\circ}$

Round 7 Component Status (X3a)
- Combined Reserve and Guard into Other

(X3a) Distribution



(X3a) Frequencies

Level	Count	Prob
Active Duty	31714	0.73790
Other	11265	0.26210
Total	42979	1.00000

(X3a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
Active Duty	1968 4.58 72.22 6.21	29746 69.21 73.90 93.79	31714 73.79
Other	757 1.76 27.78 6.72	10508 24.45 26.10 93.28	11265 26.21
	2725 6.34	40254 93.66	42979

(X3a) Tests

N	DF	-LogLike	RSquare (U)

N	DF	-LogLike	RSquare (U)
42979	1	1.8310095	0.0002

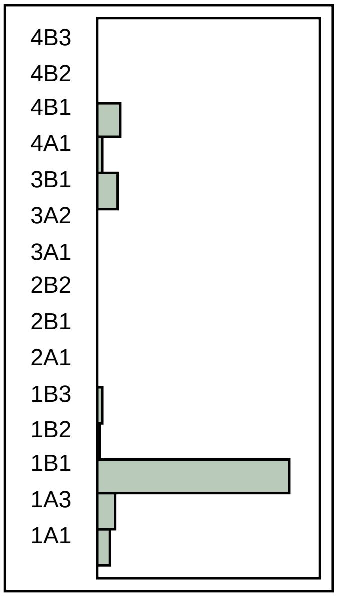
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	3.662	0.0557
Pearson	3.705	0.0543

$H_{\circ}$: Departure success (Y) is independent of Component Status (X3a)
H_a: Departure success (Y) is dependent (related to) Component Status (X3a)

- $\chi^2=\Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- α = .05
    - -- χ^2 = 3.705; P-value .0543
    - -- $\chi^2_{.05}$ @ 1df = 3.84146;
    - -- 3.705 < 3.8146; therefore – not enough evidence to reject $H_{\circ}$

Round 8 Mission Priority (X4)

(X4) Distribution



(X4) Frequencies

Level	Count	Prob
1A1	1777	0.04135
1A3	2907	0.06764
1B1	29027	0.67538
1B2	236	0.00549
1B3	634	0.01475
2A1	179	0.00416
2B1	113	0.00263
2B2	57	0.00133
3A1	80	0.00186
3A2	83	0.00193
3B1	3144	0.07315
4A1	718	0.01671
4B1	3689	0.08583
4B2	174	0.00405
4B3	161	0.00375
Total	42979	1.00000

(X4) By (Y) Contingency Table

Count	Late	On-Time	

Total % Col % Row %			
1A1	73 0.17 2.68 4.11	1704 3.96 4.23 95.89	1777 4.13
1A3	237 0.55 8.70 8.15	2670 6.21 6.63 91.85	2907 6.76
1B1	2092 4.87 76.77 7.21	26935 62.67 66.91 92.79	29027 67.54
1B2	8 0.02 0.29 3.39	228 0.53 0.57 96.61	236 0.55
1B3	47 0.11 1.72 7.41	587 1.37 1.46 92.59	634 1.48
2A1	8 0.02 0.29 4.47	171 0.40 0.42 95.53	179 0.42
2B1	3 0.01 0.11 2.65	110 0.26 0.27 97.35	113 0.26
2B2	3 0.01 0.11 5.26	54 0.13 0.13 94.74	57 0.13
3A1	4 0.01 0.15 5.00	76 0.18 0.19 95.00	80 0.19
3A2	4 0.01 0.15 4.82	79 0.18 0.20 95.18	83 0.19
3B1	129	3015	3144

	0.30 4.73 4.10	7.02 7.49 95.90	7.32
4A1	21 0.05 0.77 2.92	697 1.62 1.73 97.08	718 1.67
4B1	76 0.18 2.79 2.06	3613 8.41 8.98 97.94	3689 8.58
4B2	7 0.02 0.26 4.02	167 0.39 0.41 95.98	174 0.40
4B3	13 0.03 0.48 8.07	148 0.34 0.37 91.93	161 0.37
	2725 6.34	40254 93.66	42979

(X4) Tests

N	DF	-LogLike	RSquare (U)
42979	14	139.76936	0.0138

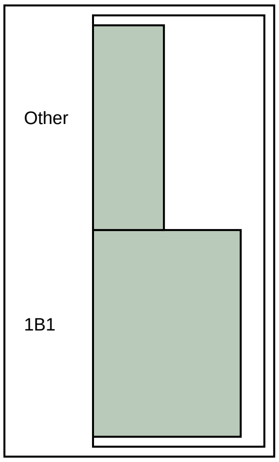
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	279.539	<.0001*
Pearson	233.520	<.0001*

$H_\circ$: Departure success (Y) is independent of Mission Priority (X4)
H_a: Departure success (Y) is dependent (related to) Mission Priority (X4)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 233.520$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 14df = 23.6848;
  - -- 233.520 > 23.6848; therefore -- strong evidence against $H_\circ$

Round 9 Mission Priority (X4a)
- Combined all Mission Priorities except 1B1 into Other

(X4a) Distribution



(X4a) Frequencies

Level	Count	Prob
1B1	29027	0.67538
Other	13952	0.32462
Total	42979	1.00000

(X4a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
1B1	2092 4.87 76.77 7.21	26935 62.67 66.91 92.79	29027 67.54
Other	633 1.47 23.23 4.54	13319 30.99 33.09 95.46	13952 32.46
	2725 6.34	40254 93.66	42979

(X4a) Tests

N	DF	-LogLike	RSquare (U)

N	DF	-LogLike	RSquare (U)
42979	1	59.795183	0.0059

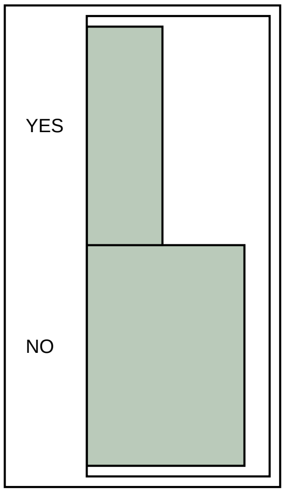
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	119.590	<.0001*
Pearson	113.129	<.0001*

$H_\circ$: Departure success (Y) is independent of Mission Priority (X4a)
H_a: Departure success (Y) is dependent (related to) Mission Priority (X4a)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
    -- $\chi^2 = 113.129$; P-value <.0001*
    -- $\chi^2_{.05}$ @ 1df = 3.84146;
    -- 113.129 > 3.84146; therefore -- strong evidence against $H_\circ$

Round 10 Primary Base (X5)

(X5) Distribution



(X5) Frequencies

Level	Count	Prob
NO	28974	0.67414
YES	14005	0.32586
Total	42979	1.00000

(X5) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
NO	1435 3.34 52.66 4.95	27539 64.08 68.41 95.05	28974 67.41
YES	1290 3.00 47.34 9.21	12715 29.58 31.59 90.79	14005 32.59
	2725 6.34	40254 93.66	42979

(X5) Tests

N	DF	-LogLike	RSquare (U)

N	DF	-LogLike	RSquare (U)
42979	1	136.53456	0.0134

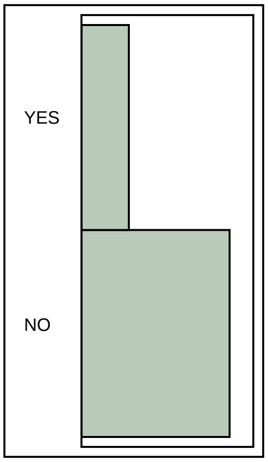
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	273.069	<.0001*
Pearson	288.297	<.0001*

$H_{\circ}$: Departure success (Y) is independent of Primary Base?(X5)
H_a: Departure success (Y) is dependent (related to) Primary Base?(X5)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- $\alpha = .05$
    -- $\chi^2 = 288.297$; P-value <.0001*
    -- $\chi^2_{.05}$ @ 1df = 3.84146;
    -- 288.297 > 3.84146; therefore -- strong evidence against $H_{\circ}$

Round 11 Departure Itinerary < 100 (X6)

(X6) Distribution



(X6) Frequencies

Level	Count	Prob
NO	32569	0.75779
YES	10410	0.24221
Total	42979	1.00000

(X6) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
NO	1837 4.27 67.41 5.64	30732 71.50 76.35 94.36	32569 75.78
YES	888 2.07 32.59 8.53	9522 22.16 23.65 91.47	10410 24.22
	2725 6.34	40254 93.66	42979

(X6) Tests

N	DF	-LogLike	RSquare (U)
42979	1	52.099783	0.0051

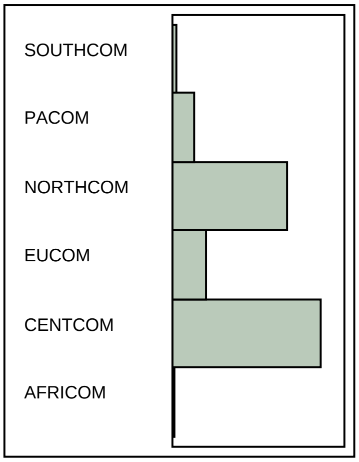
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	104.200	<.0001*
Pearson	110.945	<.0001*

$H_\circ$: Departure success (Y) is independent of Departure Itinerary < 100 (X6)
H_a: Departure success (Y) is dependent (related to) Departure Itinerary < 100 (X6)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 288.297$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 1df = 3.84146;
  - -- 110.945 > 3.84146; therefore -- strong evidence against $H_\circ$

Round 12 Departure Theater (X7)

(X7) Distribution



(X7) Frequencies

Level	Count	Prob
AFRICOM	245	0.00570
CENTCOM	19673	0.45774
EUCOM	4486	0.10438
NORTHCOM	15295	0.35587
PACOM	2831	0.06587
SOUTHCOM	449	0.01045
Total	42979	1.00000

(X7) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
AFRICOM	10 0.02 0.37 4.08	235 0.55 0.58 95.92	245 0.57
CENTCOM	942 2.19 34.57 4.79	18731 43.58 46.53 95.21	19673 45.77
EUCOM	585 1.36	3901 9.08	4486 10.44

	21.47 13.04	9.69 86.96	
NORTHCOM	994 2.31 36.48 6.50	14301 33.27 35.53 93.50	15295 35.59
PACOM	178 0.41 6.53 6.29	2653 6.17 6.59 93.71	2831 6.59
SOUTHCOM	16 0.04 0.59 3.56	433 1.01 1.08 96.44	449 1.04
	2725 6.34	40254 93.66	42979

<u>(X7) Tests</u>

N	**DF**	**-LogLike**	**RSquare (U)**
42979	5	180.63882	0.0178

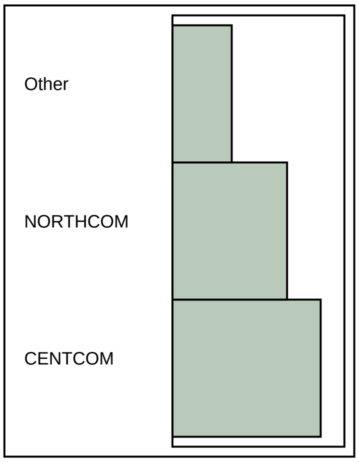
Test	**ChiSquare**	**Prob>ChiSq**
Likelihood Ratio	361.278	<.0001*
Pearson	427.536	<.0001*

H_o: Departure success (Y) is independent of Departure Theater (X7)
H_a: Departure success (Y) is dependent (related to) Departure Theater (X7)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 427.536$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 5df = 9.48773;
  - -- 427.536 > 9.48773; therefore -- strong evidence against H_o

Round 13 Departure Theater (X7a)
- Combined SOUTHCOM, PACOM, EUCOM, and AFRICOM into Other

(X7a) Distribution



(X7a) Frequencies

Level	Count	Prob
CENTCOM	19673	0.45774
NORTHCOM	15295	0.35587
Other	8011	0.18639
Total	42979	1.00000

(X7a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
CENTCOM	942 2.19 34.57 4.79	18731 43.58 46.53 95.21	19673 45.77
NORTHCOM	994 2.31 36.48 6.50	14301 33.27 35.53 93.50	15295 35.59
Other	789 1.84 28.95 9.85	7222 16.80 17.94 90.15	8011 18.64

	2725 6.34	40254 93.66	42979

<u>(X7a) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	2	115.45511	0.0114

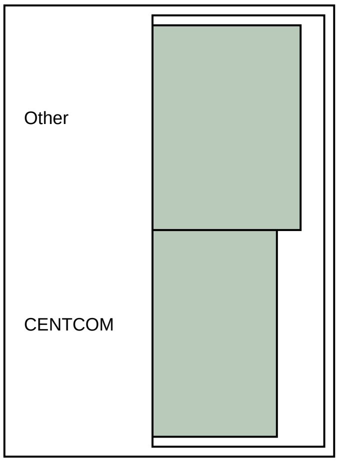
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	230.910	<.0001*
Pearson	246.522	<.0001*

$H_\circ$: Departure success (Y) is independent of Departure Theater (X7a)
H_a: Departure success (Y) is dependent (related to) Departure Theater (X7a)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 246.522$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 2df = 5.99147;
  - -- 246.522 > 5.99147; therefore -- strong evidence against $H_\circ$

Round 14 Departure Theater (X7b)
- Further combined NORTHCOM into Other

(X7b) Distribution



(X7b) Frequencies

Level	Count	Prob
CENTCOM	19673	0.45774
Other	23306	0.54226
Total	42979	1.00000

(X7b) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
CENTCOM	942 2.19 34.57 4.79	18731 43.58 46.53 95.21	19673 45.77
Other	1783 4.15 65.43 7.65	21523 50.08 53.47 92.35	23306 54.23
	2725 6.34	40254 93.66	42979

(X7b) Tests

N	DF	-LogLike	RSquare (U)

N	DF	-LogLike	RSquare (U)
42979	1	75.091493	0.0074

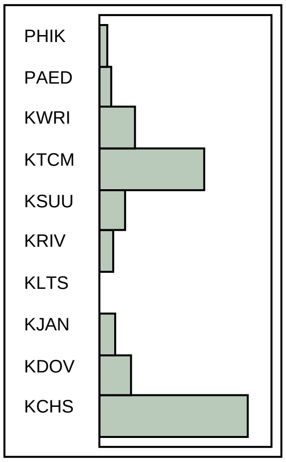
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	150.183	<.0001*
Pearson	147.160	<.0001*

$H_{\circ}$: Departure success (Y) is independent of Departure Theater (X7b)
H_a: Departure success (Y) is dependent (related to) Departure Theater (X7b)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 147.160$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 1df = 3.84146;
  - -- 147.160 > 3.84146; therefore -- strong evidence against $H_{\circ}$

Round 15 Home Base (X8)

(X8) Distribution



(X8) Frequencies

Level	Count	Prob
KCHS	16052	0.37348
KDOV	3465	0.08062
KJAN	1648	0.03834
KLTS	75	0.00175
KRIV	1511	0.03516
KSUU	2892	0.06729
KTCM	11315	0.26327
KWRI	3787	0.08811
PAED	1363	0.03171
PHIK	871	0.02027
Total	42979	1.00000

(X8) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
KCHS	984 2.29 36.11 6.13	15068 35.06 37.43 93.87	16052 37.35
KDOV	151	3314	3465

	0.35 5.54 4.36	7.71 8.23 95.64	8.06
KJAN	86 0.20 3.16 5.22	1562 3.63 3.88 94.78	1648 3.83
KLTS	2 0.00 0.07 2.67	73 0.17 0.18 97.33	75 0.17
KRIV	87 0.20 3.19 5.76	1424 3.31 3.54 94.24	1511 3.52
KSUU	123 0.29 4.51 4.25	2769 6.44 6.88 95.75	2892 6.73
KTCM	902 2.10 33.10 7.97	10413 24.23 25.87 92.03	11315 26.33
KWRI	251 0.58 9.21 6.63	3536 8.23 8.78 93.37	3787 8.81
PAED	95 0.22 3.49 6.97	1268 2.95 3.15 93.03	1363 3.17
PHIK	44 0.10 1.61 5.05	827 1.92 2.05 94.95	871 2.03
	2725 6.34	40254 93.66	42979

(X8) Tests

N	DF	-LogLike	RSquare (U)
42979	9	54.253680	0.0053

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	108.507	<.0001*

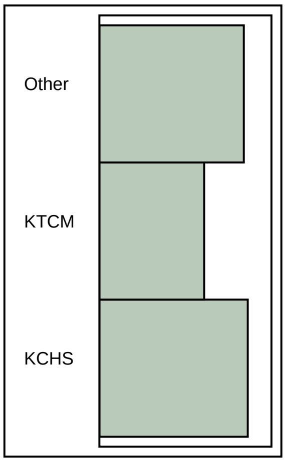
Test	ChiSquare	Prob>ChiSq
Pearson	105.989	<.0001*

$H_\circ$: Departure success (Y) is independent of Home Base (X8)
H_a: Departure success (Y) is dependent (related to) Home Base (X8)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
    - -- $\chi^2 = 105.989$; P-value <.0001*
    - -- $\chi^2_{.05}$ @ 9df = 16.9190;
    - -- 105.989 > 16.9190; therefore -- strong evidence against $H_\circ$

Round 16 Home Base (X8a)
- Combined PHIK, PAED, KWRI, KSUU, KRIV, KLTS, KJAN, and KDOV into Other

(X8a) Distribution



(X8a) Frequencies

Level	Count	Prob
KCHS	16052	0.37348
KTCM	11315	0.26327
Other	15612	0.36325
Total	42979	1.00000

(X8a) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
KCHS	984 2.29 36.11 6.13	15068 35.06 37.43 93.87	16052 37.35
KTCM	902 2.10 33.10 7.97	10413 24.23 25.87 92.03	11315 26.33
Other	839 1.95 30.79 5.37	14773 34.37 36.70 94.63	15612 36.32

	2725 6.34	40254 93.66	42979

<u>(X8a) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	2	37.062766	0.0037

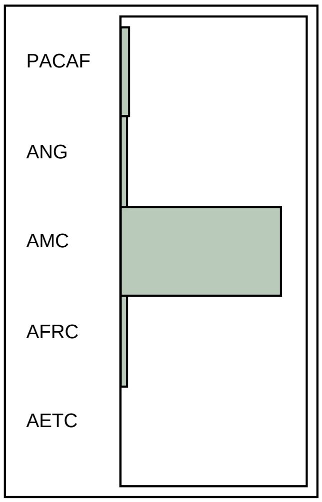
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	74.126	<.0001*
Pearson	76.453	<.0001*

H_o: Departure success (Y) is independent of Home Base (X8a)
H_a: Departure success (Y) is dependent (related to) Home Base (X8a)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 76.453$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 2df = 5.99147;
  - -- 76.453 > 5.99147; therefore -- strong evidence against H_o

Round 17 Command (X9)

(X9) Distribution



(X9) Frequencies

Level	Count	Prob
AETC	72	0.00168
AFRC	1511	0.03516
AMC	37514	0.87284
ANG	1648	0.03834
PACAF	2234	0.05198
Total	42979	1.00000

(X9) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
AETC	2 0.00 0.07 2.78	70 0.16 0.17 97.22	72 0.17
AFRC	87 0.20 3.19 5.76	1424 3.31 3.54 94.24	1511 3.52
AMC	2411	35103	37514

	5.61 88.48 6.43	81.67 87.20 93.57	87.28
ANG	86 0.20 3.16 5.22	1562 3.63 3.88 94.78	1648 3.83
PACAF	139 0.32 5.10 6.22	2095 4.87 5.20 93.78	2234 5.20
	2725 6.34	40254 93.66	42979

(X9) Tests

N	DF	-LogLike	RSquare (U)
42979	4	3.5217931	0.0003

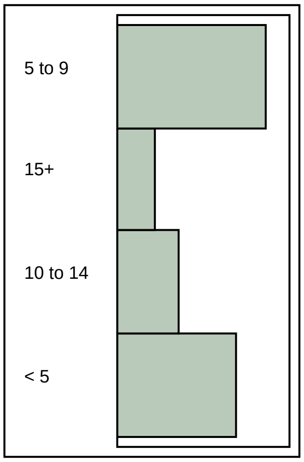
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	7.044	0.1336
Pearson	6.422	0.1698

$H_\circ$: Departure success (Y) is independent of Command (X9)
H_a: Departure success (Y) is dependent (related to) Command (X9)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 6.422$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 4df = 9.48773;
  - -- 9.48773 > 6.422; therefore – not enough evidence to reject $H_\circ$

Round 18 Age of Aircraft (X10)

(X10) Distribution



(X10) Frequencies

Level	Count	Prob
< 5	14030	0.32644
10 to 14	7136	0.16603
15+	4459	0.10375
5 to 9	17354	0.40378
Total	42979	1.00000

(X10) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
< 5	641 1.49 23.52 4.57	13389 31.15 33.26 95.43	14030 32.64
10 to 14	547 1.27 20.07 7.67	6589 15.33 16.37 92.33	7136 16.60
15+	318 0.74 11.67 7.13	4141 9.63 10.29 92.87	4459 10.37

5 to 9	1219 2.84 44.73 7.02	16135 37.54 40.08 92.98	17354 40.38
	2725 6.34	40254 93.66	42979

<u>(X10) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	3	59.650014	0.0059

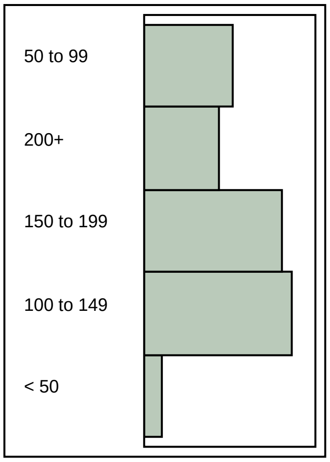
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	119.300	<.0001*
Pearson	113.620	<.0001*

$H_{\circ}$: Departure success (Y) is independent of Aircraft Age (X10)
H_a: Departure success (Y) is dependent (related to) Aircraft Age (X10)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_{α} has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 113.62$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 3df = 7.81473;
  - -- 113.62 > 7.81473; therefore -- strong evidence against $H_{\circ}$

Round 19 Aircraft Monthly Hours (X11)

(X11) Distribution



(X11) Frequencies

Level	Count	Prob
< 50	1570	0.03653
100 to 149	13570	0.31574
150 to 199	12749	0.29663
200+	6948	0.16166
50 to 99	8142	0.18944
Total	42979	1.00000

(X11) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
< 50	84 0.20 3.08 5.35	1486 3.46 3.69 94.65	1570 3.65
100 to 149	974 2.27 35.74 7.18	12596 29.31 31.29 92.82	13570 31.57
150 to 199	826 1.92	11923 27.74	12749 29.66

	30.31 6.48	29.62 93.52	
200+	331 0.77 12.15 4.76	6617 15.40 16.44 95.24	6948 16.17
50 to 99	510 1.19 18.72 6.26	7632 17.76 18.96 93.74	8142 18.94
	2725 6.34	40254 93.66	42979

(X11) Tests

N	DF	-LogLike	RSquare (U)
42979	4	25.136177	0.0025

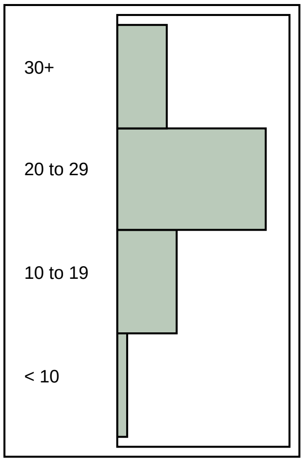
Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	50.272	<.0001*
Pearson	48.178	<.0001*

$H_\circ$: Departure success (Y) is independent of Aircraft Monthly Hours (X11)
H_a: Departure success (Y) is dependent (related to) Aircraft Monthly Hours (X11)

- $\chi^2=\Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- α = .05
  - -- χ^2 = 48.178; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 4df = 9.48773;
  - -- 48.178 > 9.48773; therefore -- strong evidence against $H_\circ$

Round 20 Delayed Discrepancy Rate (X12)

(X12) Distribution



(X12) Frequencies

Level	Count	Prob
< 10	1463	0.03404
10 to 19	9537	0.22190
20 to 29	23940	0.55702
30+	8039	0.18704
Total	42979	1.00000

(X12) By (Y) Contingency Table

Count Total % Col % Row %	Late	On-Time	
< 10	92 0.21 3.38 6.29	1371 3.19 3.41 93.71	1463 3.40
10 to 19	432 1.01 15.85 4.53	9105 21.18 22.62 95.47	9537 22.19
20 to 29	1648 3.83 60.48 6.88	22292 51.87 55.38 93.12	23940 55.70

30+	553 1.29 20.29 6.88	7486 17.42 18.60 93.12	8039 18.70
	2725 6.34	40254 93.66	42979

<u>(X12) Tests</u>

N	DF	-LogLike	RSquare (U)
42979	3	36.787874	0.0036

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	73.576	<.0001*
Pearson	68.495	<.0001*

$H_\circ$: Departure success (Y) is independent of Delayed Discrepancy Rate (X12)
H_a: Departure success (Y) is dependent (related to) Delayed Discrepancy Rate (X12)

- $\chi^2 = \Sigma$(observed frequency – expected frequency)^2/expected frequency
- reject region: $\chi^2 > \chi^2_{\alpha,}$ where χ^2_α has (r - 1)(c - 1) df
- $\alpha = .05$
  - -- $\chi^2 = 68.495$; P-value <.0001*
  - -- $\chi^2_{.05}$ @ 3df = 7.81473;
  - -- 68.495 > 7.81473; therefore -- strong evidence against $H_\circ$

Round 21 thru 76; Independent Variables vs. Independent Variables

Independent Variable Pearson Chi Squared Comparisons

	(X1b) Mission Type	(X2a) Operating Organization	(X3) Component Status	(X4a) Mission Priority	(X5) Primary Base?	(X6) Departure itinerary <= 100 from primary base?	(X7b) Departure Theater	(X8a) Home Base	(X10a) Age of Aircraft (years)	(X11a) Average Monthly Hours Flown	(X12a) Average Monthly Base_Delayed Discrepancy Rate
(X1b) Mission Type	0	12,164.6	5,675.4	15,069.8	2,134.3	1,736.5	14,617.0	5,393.6	487.2	5,212.4	4,314.4
(X2a) Operating Organization		0	14,831.6	11,788.2	3,314.7	1,409.1	21,709.8	19,195.5	3,226.1	11,480.5	14,481.6
(X3) Component Status			0	3,168.3	1,448.6	747.3	7,626.7	5,983.2	1,144.7	3,755.5	8,513.9
(X4a) Mission Priority				0	4,360.3	5,412.8	15,030.2	705.8	47.6	7,834.9	680.3
(X5) Primary Base?					0	28,417.2	8,184.1	226.6	36.9	2,042.2	264.8
(X6) Departure itinerary <= 100 from primary base?						0	6,534.4	112.4	4.5	1,698.7	84.9
(X7b) Departure Theater							0	4,432.2	549.9	8,399.7	3,473.0
(X8a) Home Base								0	9,922.0	1,586.8	37,481.7
(X10a) Age of Aircraft (years)									0	2,459.4	14,568.7
(X11a) Average Monthly Hours Flown										0	1,233.4
(X12a) Average Monthly Base_Delayed Discrepancy Rate											0

Appendix B: Analysis of Departures

Prevalence of Departures by Variables (N = 42,979)			Prevalence of Lates/Departures	
Variable	**Departures**	**%**	**Lates**	**%**
Mission Type				
Contingency	20,986	48.83%	1,479	7.05%
Other	21,993	51.17%	1,246	5.67%
Operating Organization				
385 AEG	15,737	36.62%	772	4.91%
Super Base	15,339	35.69%	1,178	7.68%
Other	11,903	27.70%	775	6.51%
Component Status				
Active Duty	31,714	73.79%	1,968	6.21%
Guard	2,619	6.09%	144	5.50%
Reserve	8,646	20.12%	613	7.09%
Mission Priority				
1B1	29,027	67.54%	2,092	7.21%
Other	13,952	32.46%	633	4.54%
Primary Base				
Yes	14,005	32.59%	1,290	9.21%
No	28,974	67.41%	1,435	4.95%
Departure Itinerary ≤ 100				
Yes	10,410	24.22%	888	8.53%
No	32,569	75.78%	1,837	5.64%
Departure Theater				
CENTCOM	19,673	45.77%	942	4.79%
Other	23,306	54.23%	1,783	7.65%
Home Base				
KCHS	16,052	37.35%	984	6.13%
KTCM	11,315	26.33%	902	7.97%
Other	15,612	36.33%	839	5.37%
Age				
< 5	14,030	32.64%	641	4.57%
5 to 9	17,354	40.38%	1,219	7.02%
10 to 14	7,136	16.60%	547	7.67%
15+	4,459	10.38%	318	7.13%
Monthly Hours				
< 50	1,570	3.65%	84	5.35%
50 to 99	8,142	18.94%	510	6.26%
100 to 149	13,570	31.57%	974	7.18%
150 to 199	12,749	29.66%	826	6.48%
200+	6,948	16.17%	331	4.76%
Delayed Discrepancy Rate				
< 10	1,463	3.40%	92	6.29%
10 to 19	9,537	22.19%	432	4.53%
20 to 29	23,940	55.70%	1,648	6.88%
30+	8,039	18.70%	553	6.88%

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14. ABSTRACT This research analyzes twelve independent qualitative variables and one dependent qualitative variable for the C-17A Globemaster III. JMP, version 10, and Excel are used to analyze data from 1 October 2009 thru 31 August 2010. Contingency Table analysis and backward stepwise logistic regression are used to determine which factors most strongly predict C-17A aircraft reliability behavior. Qualitative data is extracted from the Global Decision Support System II, Logistics, Installations and Mission Support-Enterprise View, and the Core Automated Maintenance System for Mobility/G081. The model does generate tangible statistical values but with very little practicality and suggests aircrafts monthly hours, mission type, or component status have the weakest associations with departure reliability.			
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